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January 31, 2005

"Multi-disciplinary Computational Tools for Naval Design"

Sponsored by Office of Naval Research under STTR program

Order No N00014-04-M-0306

Name of Contractor: **Mechmath LLC**

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Effective Date of Contract: July 1, 2004

Contract Expiration Date: February 1, 2005

Short Title of Work: **Final Report**

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE *(DD-MM-YYYY)*
1 February 2005

2. REPORT TYPE
Final Report

3. DATES COVERED *(From - To)*
July 1, 2004-February 1, 2005

4. TITLE AND SUBTITLE
Multi-disciplinary Computational Tools for Naval Design

5a. CONTRACT NUMBER
Contract No N00014-04-M-0306

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Eduard Amromin

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Mechmath LLC
14530 Bluebird Trail, Prior Lake, MN 55372-1283

8. PERFORMING ORGANIZATION REPORT NUMBER
FR-N05

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Navy
Office of Naval Research
800 North Quincy Street
Arlington VA 22217-5660

10. SPONSOR/MONITOR'S ACRONYM(S)
Navy

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
0001AC

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; STTR report, distribution unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
The general aim of Naval Design (ND) is to make a ship able to perform some prescribed mission. There is a combination of restrictions related to physical interaction of the warship and sea with others that have a military background. As a result, the ND combines numerous tasks and requires tremendous computations, but optimization of computations is a challenge because ND is a multi-criterion problem. Project delivers the complete succession of mathematical fundamentals of ND. Instead of traditional design spiral, a hierarchy multi-level design system is considered. The concept of criterion coordination with Lagrange multipliers is described. The feasible design solutions are studied with the Pareto sets. Comparison of Pruning and Constructive algorithms in grid generation is given, as well as description of LP-tay sequencing in this generation. The developed approaches are illustrated by examples of multidisciplinary ND recently considered in scientific publications. Additionally, a background of multidisciplinary trimaran optimization is developed.

15. SUBJECT TERMS
Multi-disciplinary multi-criterion optimization. Coordination of controversial solutions. Pareto sets. Feasible designs. Interpolation of solutions of complex physical problems on grids generated with LP-tay sequences. Examples of multi-criterion naval design.

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
U	U	U	SAR	35	Eduard Amromin
					19b. TELEPHONE NUMBER *(Include area code)* (952)-402-9642

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

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8. PERFORMING ORGANIZATION REPORT NUMBER. Enter all unique alphanumeric report numbers assigned by the performing organization, e.g. BRL-1234; AFWL-TR-85-4017-Vol-21-PT-2.

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10. SPONSOR/MONITOR'S ACRONYM(S). Enter, if available, e.g. BRL, ARDEC, NADC.

11. SPONSOR/MONITOR'S REPORT NUMBER(S). Enter report number as assigned by the sponsoring/ monitoring agency, if available, e.g. BRL-TR-829; -215.

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EXECUTIVE SUMMARY

The general goal of Naval Design (**ND**) is to make a ship able to perform some prescribed mission. There is a combination of restrictions/constrains and criteria related to physical interaction of the ship and sea with others that have either military or commercial background. Therefore, ND combines numerous tasks which are carried out in the framework of separate disciplines. The traditional design concept called as the Spiral Design uses optimization results obtained from a preceding discipline in constrains for the next optimization problem. The convergence of the Spiral Design is usually achieved by an intuitive decision of the designer and associated with his/her individual experience.

Considering other concepts of Multi-Disciplinary Computations (**MDC**) in ND, we evaluated Multi-Level Hierarchy System (**MLHS**) approach as the best concept because MLHS allows coordination of the solutions obtained within different major disciplines and design subsistems. Besides, MLHS makes it possible to substantially reduce the tremendous amount of the overall system variables and number of variants analyzed with complex mathematical models (CFD, BEM and FEA).

The entire succession of mathematical issues associated with employment of MLHS to MDC in ND is analyzed in this Final Report:

- The coordination of solutions obtained in different disciplines with employment of Lagrange multipliers is described and illustrated by an example of ND.
- Because ND problems are substantially multi-criterion problems, numerous constrains significantly reduce feasibilities of design solutions. As explained, the designer decisions on selection of a compromise between controversial criteria should be made with consideration of the Pareto set. The Parameter Space Investigation (**PSI**) method is applied here to determine feasible designs and this set. Applicability of PSI method is demonstrated for series of preliminary ND tests and validated by comparing with results of publications, where multi-criteria optimization problem was solved by converting into a single-criterion optimization It is shown that the usual geometry of feasible areas in variables space of ND is too complex (indented) for application of gradient-based minimization techniques, and the preference should be given to some random search.
- Because of high computational expenses in ND, selection of variables, generation of computational grids/nets and approximation of computational results are exclusively important. Comparison of Pruning Algorithms (**PA,** which require preliminary grid generation) and Constructive Algorithms (**CA,** which do not require it) is performed. Neural Network generated by Cascade Correlation technique is considered as an example of CA. The LPτ-sequence technique of grid generation for PA is also described and evaluated.

Comparison of PA and CA is illustrated by examples of ND which contain coupling of complex hydrodynamic problems solved with CFD and BEM codes with simple restrictions obtained from other disciplines. This comparison manifested the advantages of PA combined with interpolation of preliminary obtained results in reasonably selected variables. An approach for matching complex solvers of physical problems with multi-variable solvers of other design problems is elaborated.

Examples of MDC in ND for problems recently considered in the scientific publications illustrate application of the selected approaches to MDC with three criteria and constrains related to many different disciplines. ND problems for a bulk cargo carrier and for a frigate have been studied. The frigate model was implemented in MATLAB. Several customized modules were developed and compiled into a set of dynamic link libraries to allow an interface between PSI and this ship model. Formulation of multi-disciplinary naval design problems for a trimaran finishes this Phase I project as an undertaking for the eventual Phase II project.

Naval Postgraduate School and California State University (Long Beach) have contributed to this project as subcontractors.

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2. INTRODUCTION

The general aim of naval design is to make a ship able to perform some prescribed mission. Such mission may require carry the certain number of helicopters along a given length route in seas with some limitations on minimum of speed, possibility to locate some guns over the deck, etc. The primary designer goal is basically to distribute these helicopters, guns, the necessary machinery, crew compartments, etc within a shell/hull. The results of interaction of this shell with the sea (hydrodynamic drag, noise, etc) depend on the shell shape and critically affect the ability of the ship to perform the prescribed mission. Thus, there is a combination of some restrictions related to physical interaction of the warship and sea with others that have a military background. As a result, the naval design combines numerous tasks which are traditionally carried out in the framework of separate disciplines. This design is certainly a complex kind of Multi-Disciplinary Optimization (**MDO**).

Naval design process is a specific kind multi-criterion optimization that cannot be improved simultaneously by all criteria. For example, the maximum effectiveness does not correspond to the minimal cost. Further, the design process cannot be modeled in the frame of the single mathematical model with a solely variable set. The design process must be modeled as set of mathematical models, which constitute the Design system of models correspondent to the different design subtasks. These subtasks are in the logical hierarchy, when some of the subtasks use the multiple input of the preceding subtasks and produce the multiple output data for the subsequent subtasks. Therefore, the concept of the Multi Level Design System (**MLDS**) adequately reflects the specifics of the naval design process.

It is very often in naval design that the tasks are not well defined from the beginning of the design process: Some of the design restrictions, dependent of many variables and input data can lead to the empty feasible design set, some of the criterions can be correlated with each others and complicate the optimization process. The analysis of the correlation factors within the task mathematical models, analysis of the functional dependence of different variables and similar “model testing and analysis” has to be provided in the optimization process. The optimization algorithms must be adaptive to such “model testing and analysis”. Problems of ship hull optimal design have received considerable attention in many contexts, and substantial results have been received for ship hydrodynamics (like presented by Amromin, Mizine et al, 1983; Day & Doctors, 1997; Schmitz et al, 2004), acoustics, etc. However, the general aim of ship design requires an overall multi-disciplinary optimization, and the challenge is that the automatic optimization procedures for ship design haves not yet reached the same maturity, though such optimization is a topic of high interest during the recent years (by Peri & Campana, 2003; Peacock et al, 2003; Parsons & Scott, 2004)

The challenge is that connections between the different disciplines are quite complex and because of this, the analysis in each discipline is traditionally performed separately. The results obtained from a previous discipline predetermine constrains for the successive optimization problem. As a result, very small possibilities are left to the last optimization problem because an initial problem dominates in the final solution. This traditional approach is called as the Spiral Design. The convergence of the Spiral Design is usually achieved by an artificial, intuitive interaction with the professional designer and associated with the direct use of his/her individual experience and historical data. So, for the Spiral Design, the optimization results also substantially depend on the designer experience.

In the present project, the numerical optimization will be developed on the basis of an alternative approach that couples the involved disciplines. This approach is called Multi Level & Multi-Disciplinary Optimization (**ML&MDO**). Mathematically, it is optimization with multiple, non-contradictory criterions. Improvements in some of them may result in a deterioration in performance of the system, and criteria constrains have to be introduced. In the present approach, the multi-objective nature of the ship design is kept in mind and we will refer to ML&MDO in the sense of multi-objective optimization.

Considering different optimization concept, we found out that the Multi-Level Hierarchy System Approach does not have reliable alternative because of the tremendous amount of input/output data and of the overall system variables, and tremendous complexity of the mathematical models including sophisticated CFD and FEA tools. This modern approach was first originated in the large decision-making economical systems and then was applied to various technical design systems. ML&MDO methodology was first applied to the aircraft design problems (Statnikov & Matusov, 1995). Since mid 90^{th}, application of ML&MDO to diverse branches of engineering has become more and more frequent. ML&MDO techniques would supply the Navy designer with valuable tools for solving the complicated ship design problems at synthesis and analysis phases. The validity of the methodology can be demonstrated for innovative ships for different commercial and military applications.

The Phase I project is emphasized on the basic issues of MDO. The following issues are considered:

- First, the necessity to coordinate the design solutions made at different levels of hierarchy in different subsystems of the Naval MLDS is critical. This coordination mathematically is proven and practically viable, as was shown in sample models.
- Second, the practical ship optimization problems are usually multi-variable/parameter problems with non-convex allowable domains in the variable spaces, so the gradient calculations become very expensive if possible. Methods of Parameter Space Investigation (**PSI**) back affordable alternatives for gradient calculations.
- Third, there are accurate enough commercial solvers for different physical/engineering problems related to naval design, but their complicity and requirements to computer resources makes it unpractical to employ such solvers in inherently many-steps optimization procedures. This issue would be avoided by combination of rational grid generation and interpolation techniques.

Further, some simplified examples of MDO in Naval design are prepared as demonstration here, and some advance in formulation of MDO for trimaran is also presented here. The engineering algorithms and software for practical implementation in different naval designs would be developed in Phase II.

3. Coordination of Design Solutions in Multi-Level Design systems

Usual optimization approach for design problems is based on Operational Research principles. There are several phases in the Operational Research:

- Definition of the design optimization task;
- Selection of variables and restrictions for the output parameters;
- Development of the algorithm – task solver;
- Analysis of the solution.

This approach mostly corresponds to the step-by-step, package-type mode of computer calculations within the unique mathematical model of the optimization problem and cannot be efficiently used for ship design problems, which involve very complicated computational models for various specific disciplines, such as hydrodynamics, structural acoustics, etc.

The suggested Multi-Level Design Decision-Making System is based on mathematical modeling of the design subtasks and Multi-Level Hierarchy System. Each subtask, regardless how it is completed, produces the local solutions related to subsystem. Each subtask has its own variables; the amount of which is less that the total amount of the whole system variables (this achieves the obvious goal of reduction the parametric space). In ship design, such subsystems are traditionally hull forms development, structural, machinery and propulsion parts of the ship platform design process. In the Multi-Level Hierarchy System the Spiral Design approach is substituted by a methodology that allows a proper coordination of the local solutions obtained in the subsystems. This coordination has to be provided for

the interest of the whole System. The general MDO approach can be formalized as the following mathematical problem:

$$\mathbf{Min\{F(X) = (f_1, f_2,\ldots,) \mid G_1(X)<0, G_2(X)<0\ldots.\}} \qquad (1)$$

Here $\mathbf{G_1}$, $\mathbf{G_2}$,…are the design restrictions**,** where **X** is the vector of design variables, $\mathbf{f_1}$ =1/[Global Mission Efficiency], $\mathbf{f_2}$ = Total Life Cost, $\mathbf{f_3}$ =Powering, $\mathbf{f_4}$ =Structural Weight, $\mathbf{f_5}$ = 1/[Payload & Cargo Volumes], etc. The traditional "design spiral", on which MDO in Naval Design is currently based on is illustrated in Figs.1 and 2. Such a spiral includes package-type iterative computations that are not usable for synthesis. Besides, there is no mathematically proven convergence of iterations.

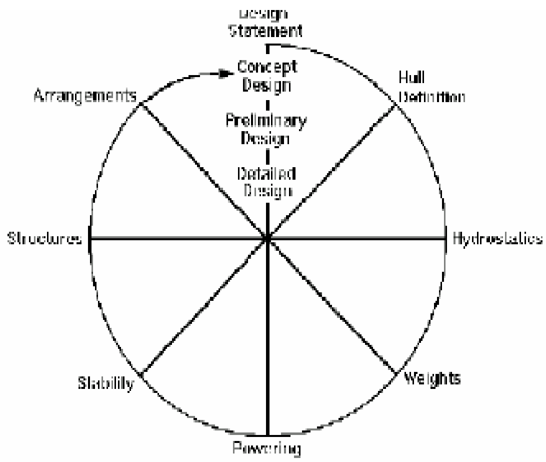


Figure 1: "Design spiral" in Naval MDO

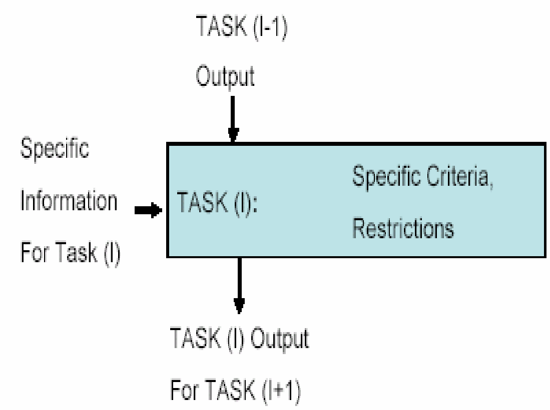


Figure 2: Information flows in the "Design spiral"

From mathematical point of view, iterations compose an infinite succession that has no limit. However, as stated by Cauchy-Weershtrass theorem, a partial sub-succession can be selected from such infinite succession, and this sub-succession will have the certain limit. The above-mentioned termination of iterations due to a designer arbitrary selection corresponds to the mentioned sub-succession, but not on to the iteration convergence upon formalized criterion.

The mathematical convergence in Multi Level Design System (MLDS) is achieved by coordination of design solutions from the point of the overall/global efficiency. Mathematical coordination is based on Theory of Games with non-contradictory interests and on modification of Local Task (I) criteria by adding special terms to measure Global System, Task (0) criteria change depending on Task (I) variables. The MLDS scheme is shown in Fig. 3.

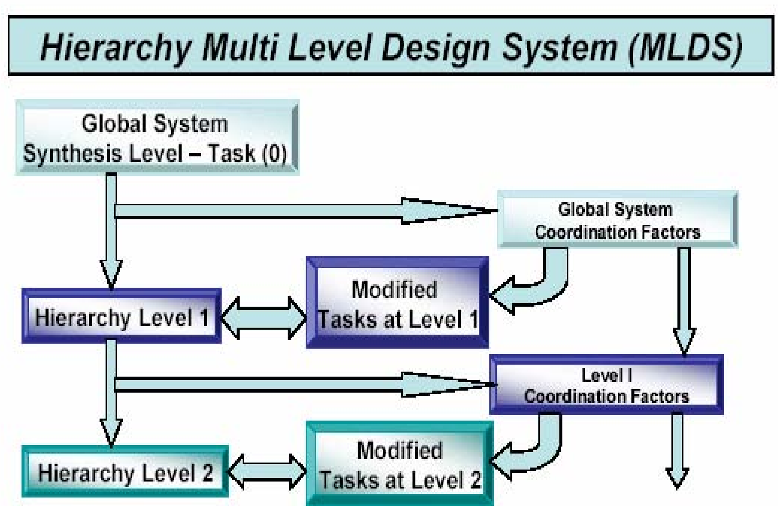


Figure 3: A simplified scheme of MLDS

3.1 Impact of Subsystems of Lower Hierarchy on Global System Criteria

The subsystem design has the goal to increase the global system efficiency. For achieving this goal, the designer needs algorithms calculating the impact of local design solution on the global design system criterions. It was shown (Graham, 1975) that for such goal the so called local criterions have to be developed and used in the optimization process. An acoustic system was presented as an example in the following assumptions: The ship has no reserves on areas, volumes, power and displacement margin; it is also not allowable to reduce her speed or range. The weight of the acoustic system is 60 tons; the required electric power is 100Kw; the additional personnel 8 people; the required deck area 1,500 ft^2.

The first cycle of subsystem design showed that the ship displacement increases by 200 tons due to installation of the acoustic system. The power of machinery requires an increase and, as result, its weight has to be increased by 2 tons. The needed area would increase by 200 SQFT. Additional required fuel is 12 tons and additional tanks capacity is 550 ft^3. Additional personnel for 8 people would increase ship displacement for 40 tons. Bow bulb for acoustic system increases resistance at economical speed. That would require 150 tons of additional fuel and 6100 $ft^3$for the fuel tank, etc. Finally, the overall increase of ship displacement due implementation of a 60-ton acoustic station is 600 tons. This example shows how complex is the subsystem impact on global system parameters and criterions.

3.2 The Coordination Lagrange Multipliers for Subsystem Optimization Criterions

Let us define the vector of design variables as $\mathbf{X=(X_0, X_k)}$, where $\mathbf{X_0}$ is the design variables of the Synthesis Level TASK 0 (see Fig. 3) and $\mathbf{X_k}$ is the design variables of any k-subsystem at the next level of hierarchy (Level 1 in Fig. 3). The vector $\mathbf{X_0}$ can include the main ship dimensions, characteristics of general arrangement (number of holds, etc), ship configuration parameters, etc. For k=1,) $\mathbf{X_k}$ means hull forms parameters, parameters of propulsion system, etc (Subsystem of Hull forms and Propulsion design). For k=2, $\mathbf{X_k}$ means scantling characteristics, material parameters, etc (Subsystem of ship structure design).For k=3, , $\mathbf{X_k}$ means power distribution characteristics, etc. (Subsystem of mechanical design). We define the Global System Efficiency Vector by

$$\mathbf{Min\{F(X) = (f_1, f_2,\ldots,)\}}$$

where each $\mathbf{f_1,f_2,\ldots,=\{f_m,\ m=1,\ldots M\}}$ would also depend on $\mathbf{X=(X_0, X_k)}$ and $\mathbf{K}$ is the number of design subsystems. Design restrictions

$$\mathbf{G_1(X)<0,\ G_2(X)<0\ldots}$$

would also depend on $\mathbf{X=(X_0, X_k)}$. Multi Level Design System approach assumes that it is impossible to solve optimization problem with all variables X based on a global mathematical model and the design process is based on decomposition of the global optimization model into different levels of Hierarchy System, as it is shown in Fig. 3. At the first "0-level" of system hierarchy we solve the global synthesis Task 0 with variables $\mathbf{X_0}$. Parameters $\mathbf{X_k}$ are fixed: $\mathbf{X_k= \underline{X_k}}$. Correspondingly at synthesis level we solve

$$\mathbf{Min\{F(X_0, \underline{X_k})\ |\ G_l(X_0, \underline{X_k})<b_l,\ l=1,\ldots,L\}}$$

where $\mathbf{L}$ is the amount of design restrictions of different types; $\mathbf{b_l}$ – is the design limits of the restrictions.At the "1-level" of system hierarchy we solve each of the subsystems optimization tasks for $\mathbf{X_k}$, k-1,…,K at fixed global vector $\mathbf{X_0=\underline{X_0}}$. Correspondingly,

$$\mathbf{Min\{Fk(\underline{X_0}, X_k)\ |\ g_k(\underline{X_0}, X_k)<b_k\}}.$$

This decomposition scheme reflects the obvious design practice: Developing the hulls forms, a designer uses given main dimensions of the ship, which are previously defined at a synthesis level of design system. The same will be with structural design, mechanical design and so on. The subsystem

impact on global vector of efficiency can be illustrated for one of the criterions $\mathbf{F(X_0, X_k)}$ in Fig.4. Let us assume that vector $\mathbf{X_0=(x_1,x_2)}$, where x_1 is block coefficient and x_2 is B/T, beam to draft ratio.

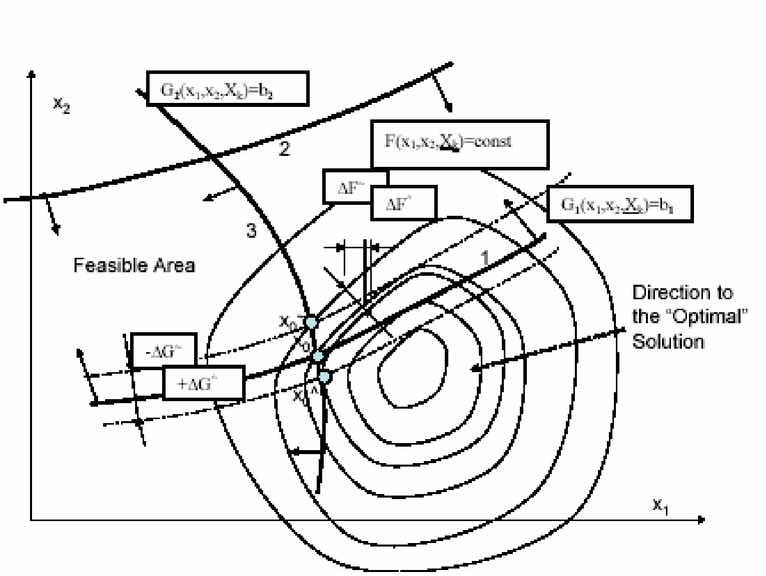


Figure 4: Interaction of synthesis and "1-level" design subsystem.

The constrain $\mathbf{G_1(x_1,x_2,\underline{X}_k)=b_1}$ corresponds to the lower limit of the stability constraint (minimum metacentric height), $\mathbf{G_2}$ is the upper limit of initial stability, $\mathbf{G_3}$ is the payload/volume capability. Functions $\mathbf{F}$ and $\mathbf{G_1}$, $\mathbf{G_2}$, $\mathbf{G_3}$ depend on $\mathbf{x_1}$ and $\mathbf{x_2}$ at fixed $\mathbf{\underline{X}_k}$. Dashed line is the change of the boundary $\mathbf{G_1}$ when the parameters $\mathbf{X_k}$ becomes not equal to the $\mathbf{\underline{X}_k}$. It happens at optimization of the k-subsystem at "1-level" of hierarchy after optimization at synthesis level. These changes can extend ($+\Delta G^{\wedge}$) or reduce ($-\Delta G^{\sim}$) the feasible area of solutions at synthesis level of hierarchy.

Correspondingly, either $\Delta F^{\wedge}$, or $\Delta F^{\sim}$ are the changes of synthesis level efficiency criterion as result of extension or reduction of the feasible area of design solution. Figure 4 shows the design interpretation of the Lagrange dual multipliers $\boldsymbol{\lambda}$, which are determined as $\boldsymbol{\lambda_l=\Delta F/\Delta G_l}$, $\mathbf{l=1,\dots,L}$ and are calculated in the assumption that $\mathbf{X_k}$ can be unequal to $\mathbf{\underline{X}_k}$ at $\mathbf{\underline{X}_0}$, determined in Task 0.

3.3 Modification of the Design Subsystems to achieve coordinated strategies within MLDS

The Lagrange dual multipliers can be used for coordination strategies between the levels of the MLDS. The coordination is provided by special modification of the criterions of the "lower-level' design subsystems. The requirements for such modification are the following:

- Modified "lower-level" criterion should lead to such "local" solutions $\mathbf{X_k}$, which are most favorable from the point of the global system efficiency criterions $\mathbf{F(\underline{X}_0, X_k)}$
- "Local" criterions should penalize such $\mathbf{X_k}$, which reduce the feasible area in the "synthesis-level" Task 0 (see Figs. 3 and 4) and stimulate such $\mathbf{X_k}$, which increase this area.
- Calculation of the "local" criterions should be possible with minimum information from other subsystems because the optimization of subsystems is provided in parallels for all **K** subsystems at each level of hierarchy.

The only coordination factors for local criterions would be Lagrange coefficients $\boldsymbol{\lambda_l}$, which can be calculated in synthesis-level optimization task. The special form of the "local" criterion would be the following:

$$\mathbf{\Phi_k=F_k(\underline{X}_0, X_k)+\sum \lambda_l*\Delta G_l(\underline{X}_0, X_k)} \tag{2}$$

The sum operation is provided for each index l=1,…,L of synthesis-level constraints, which at point $\mathbf{\underline{X}_0}$ are the equalities. For the example in Fig.4, the constraint with number l=2 would not be included in (2) because lower and higher limits of initial stability cannot be realized simultaneously. In other words, we can say that for the constraints which are in point $\mathbf{\underline{X}_0}$ not the equalities, Lagrange coefficients $\boldsymbol{\lambda_l}$ are equal to zero. The employment of $\mathbf{\Phi_k}$ in lower-level subsystems optimization allows coordination of design solutions at the different levels of MLDS. Coordination factors are calculated in synthesis-level

optimization task for each of the global constraints as partial derivatives $\lambda_l = \partial F / \partial G_l$ and then λ_l are used at lower-level design subsystems optimization with modified "local" criterions (2).

3.4 Calculation of the Coordination Factors

We will show several calculations of the λ_l. Let us consider "synthesis-level" model with

$$\mathbf{X_0}=(x_1,x_2,x_3)=(\text{Block Coefficient, Length to Beam Ratio, Beam to Draft}).$$

The feasible area is determined by constrains, which include Weight, Volume Balance, Initial Stability, etc. The initial data for the general cargo ship was the following:

- Payload = 11,530 t;
- Machinery Power = 6,600 kW;
- Cargo fraction = 1.86 M^3/t;
- Required Range = 13,200 NM.

The results of Coordination factors calculations are presented in Figs. 5, 6, 7 and 8. These results are calculated as partial derivative of economical criterion, which is the Ratio of Building Cost to Amount of Annual Cargo, \$/ton, to different design constrains and input data l=1,…,L.

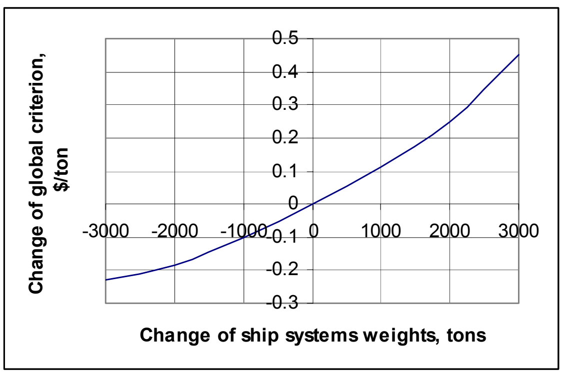


Figure 5: Economical criterion versus ship weight. For this case, the optimal draft is less than minimal constraint. Relative cost of ship weights is 0.000115 [$/t/t] or 9.55 $/t.

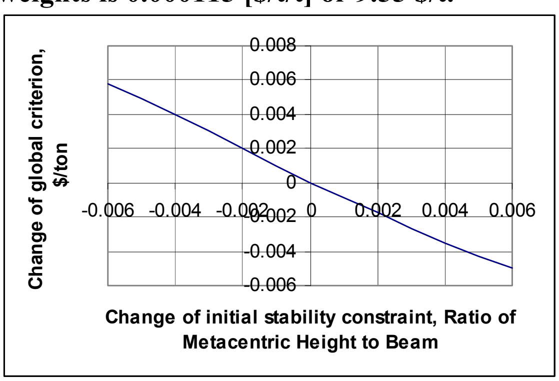


Figure 6: Economical criterion versus ship initial stability. Relative cost of initial stability is 0.000475[$/t/h/B], or 39.5 $/centimeter. Here h is metacentric height.

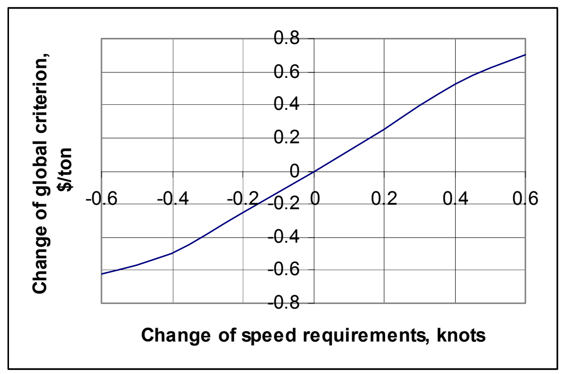


Figure 7: Economical criterion versus ship speed. Relative cost of speed, [$/t / kn] is 1.30, or 108,000 $/knot.

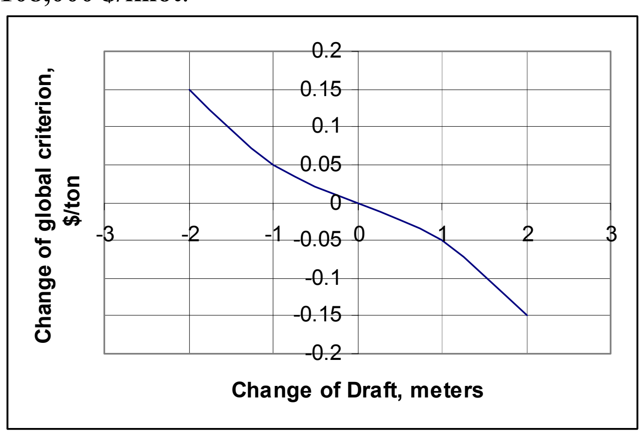


Figure 8: Economical criterion versus maximum draft. Relative cost of draft is 0.04 [$/t / m] or 95,000 $/meter.

Similar calculations can be performed with other design constrains and other global criteria. These coordination factors assumed to be known in the course of the subsystems optimization, allowing modification of the local criterions and ensuring the coordination of local design solutions in respect of the global criteria of MLDS. The mathematical background and formulation of conditions of convergence for such type of coordination strategy is provided by Germeir (1976) and Mizin & Pashin (1994).

<u>Summary of Coordination Strategies for MLDS</u>: The Coordination Strategies employ the Lagrange Dual Multipliers. These Multipliers has the clear technical (or economical) sense: They measure the "price" of changing the system overall constrains, providing the local subsystem tasks by the necessary information about the overall system interests and helping to provide optimization in the subtask corresponding to overall system criterions and interests. This approach under certain assumptions and with special form of modifying local criteria (2) has the proved convergence for the overall Hierarchy System and enables coordination of the local solutions. The further use of the Theory of Games with Non Contradictory Interests helps also to organize the optimization process in the parametric spaces of local subsystems with their sets of design parameters of much less dimensions than the overall Design System.

4. Selection of Variables and Parameter Space Investigation

Selection of variables is one of central points of any optimization because the possibility of optimization within a reasonable time critically depends on computation reduction due an effective selection of variable space. Looking for the best variables in naval design, one must keep in mind that the optimal naval design is basically determination of the best geometry of the ship and her parts. Determining such geometry, a designer has to solve problem of two different classes and do a coordination of the solutions.

One class of problem can be named as physical problems because these problems describe interaction of the ship hulls with the surrounding medium. Their formulations in Hydrodynamics, Acoustics, Structural Mechanics, Electrodynamics, etc result in differential and integral equations with continuous coefficients and some fixed parameters. Their solutions are generally continuous functions of continuous variables. Although an accurate solving of such problems with Computational Fluid Dynamics (**CFD**) codes, Boundary Element Methods (**BEM**) codes or Finite Element Analysis (**FEA**) codes is time-consuming, their solutions usually smoothly depend on geometrical characteristics of the ship hulls. Therefore, for a well-selected set of hull geometric parameters as a vector of variables, one can synthesize the new designs with interpolations of such solutions in the necessary points of variable/parameter space.

Another class of problem can be named as distribution problems. There are many boxes of fixed sizes which must be distributed within the hull (from engines to bunks). The solutions of such problems depend on discrete values of numerous variables. Thus, the solutions are also discrete though their values should be calculated with some dispersion (as prescribed by *Six Sigma* methodology because sizes of boxes or their weights have some dispersion due to manufacturing reality). Computation of minimized functions and constrains for such problems in a solely point of variable space does not look time-consuming, but enormous number of points must be analyzed during optimization.

Commonly used mathematical optimization methods have been based on gradient calculations, but such methods are not suitable for the practical naval design processes because of the above-mentioned coexistence of two very different classes of problems. Combined consideration of physical problems and distribution problems is necessary in MDO because different distributions may require some variations of hull shape and physical consequences of such variation must be determined. However, their simultaneous solving would be certainly an overspending of computer resources and interpolation of preliminary obtained solutions of physical problems would be included in a reasonable algorithm. The challenge is to minimize the number of variables and the grid size for physical problems.

Fortunately, solutions of physical problems are usually smooth enough and depend mainly on several geometrical parameters of the ship hull (This fact is already used in generalizations of empirical data for ships by Holtrop & Mennen (1982) and others). For example, the wave resistance coefficient C_W of monohulls at a fixed value of Froude number Fn depends mainly on the hull slenderness L/B, its block coefficient C_B, beam to draft ratio B/T and ratio of bow bulb displacement to the total ship displacement D_b/D. Realistic variations of these parameters associated with feasible variations of other design parameters are usually much less than ±10%, and smooth influence of these parameters on C_W make it possible to prepare only 3×3×2×2=36 values for the future interpolations.

Thus, there is a necessity to separate feasible and non-feasible designs. As a result of the assessment of different methodologies, we have chosen the Parameter Space Investigation (**PSI**) method. The PSI method allows solving the Multi-Criteria Optimization (**MCO**) problems with complex mathematical models, providing different types of analysis. The PSI method was originally developed in early 80th in the Soviet Academy of Science by Dr. R. Statnikov and Prof. L. Sobol and initially was applied for machinery optimization and aircraft CAD systems. For ship design, this method was first employed by Dr. I. Mizine in 80th. The PSI method can be used for diverse applications that include:

- Design;
- Identification;
- Operational Development of Prototypes;
- Optimization of Large-Scale Systems.

The general formulation of MCO Problems is following: There are the design variables in the simplex limited by the constraints defined below:

$$\alpha_j^* \le \alpha_j \le \alpha_j^{**}, \quad j = 1,\ldots,r. \tag{3}$$

There are also functional constraints which may be written as:

$$C_l^* \le f_l(\alpha) \le C_l^{**},\ l = 1,\ldots,t. \tag{4}$$

The criteria constraints are given by:

$$\Phi_\nu(\alpha) \le \Phi_\nu^{**}, \quad \nu = 1,\ldots,k. \tag{5}$$

Constraints (3), (4) and (5) define the feasible solution set D. The basic problem of MCO is to find the set P$\in$D for which

$$\Phi(P) = \min_{\alpha \in D} \Phi(\alpha) \tag{6}$$

Here $\Phi(\alpha) = \left(\Phi_1(\alpha),\ldots,\Phi_k(\alpha)\right)$ is the vector of criterion values and P is the so-called Pareto optimal set. Note that this formulation and PSI methodology does not require explicit mathematical formulas for criteria and functions. Both criteria and functions can act as "black boxes", but the practical application of the PSI methods requires determination of the constraints $\alpha_j^*, \alpha_j^{**}$, C_l^*, C_l^{**}, Φ_ν^{**} which would define the feasible solution set $D = \{\alpha_j^i \mid \alpha_j^*, \alpha_j^{**}\ C_l^*, C_l^{**}, \Phi_\nu^{**}\}$.

Let us consider a problem with two design variables, two functions and two criteria as an example of construction of a feasible solution set. We want to construct feasible solution set. We impose design variable constraints: $\alpha_1^* \le \alpha_1 \le \alpha$ and $\alpha_2^* \le \alpha_2 \le \alpha_2^{**}$, as well as functional constraints $C_1^* \le f_1(\alpha) \le C$ and $C_2^* \le f_2(\alpha) \le C_2^{**}$. This gives us a subset G (G$\in\Pi$). Finally, we impose criteria constraints: $\Phi_1(\alpha) \le \Phi_1^{**}$ and $\Phi_2(\alpha) \le \Phi_2^{**}$. This yields feasible solution set D (D$\in$G$\in\Pi$) shown in Fig. 9.

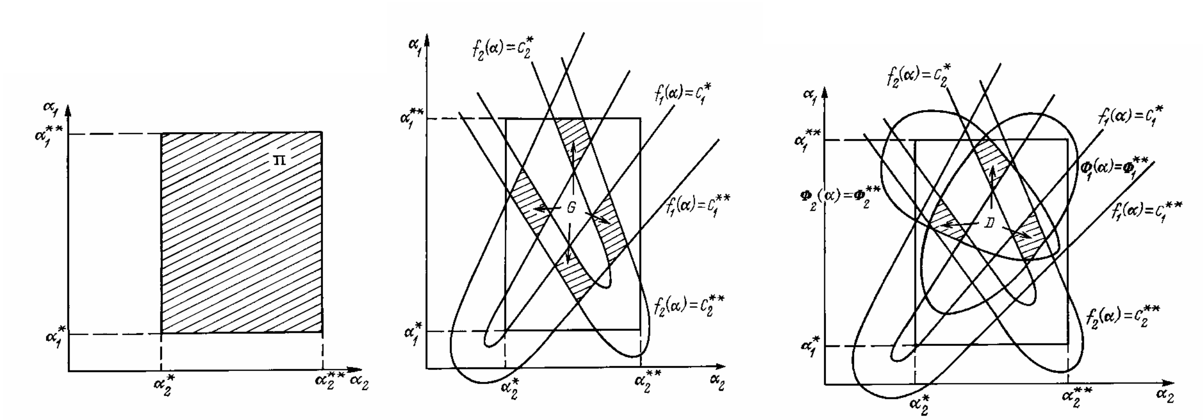


Figure 9: Feasible space D. In the accordance with Eq.(3), design variable space is the parallelepiped Π. Constrains (4) and (5) reduce it to combination of three distinct areas shadowed in the right part of the plot.

There are two basic Single-Criterion Approaches for MCO. The first one is substitution of a multitude of criteria by a single criterion with weighs $\Phi = \beta_1\Phi_1(\alpha) + \ldots + \beta_k\Phi_k(\alpha)$. The second one is optimization of the most important criterion $\Phi_1(\alpha) \rightarrow \min$, under constraints (3), (4) and modified constrain (5) in the form $\Phi_\nu(\alpha) \leq \Phi_\nu^{**}, \nu = 2,\ldots, k$. However, the substitution of a multitude of criteria by a single criterion does not answer:

- How to determine weighting coefficients?
- Why do we need to consider a linear combination of weighting coefficients and criteria?
- How to normalize criteria in order to sum and multiply them?

On the other hand, the optimization of the most important criterion does not answer:

- Is this criterion the most important? (In the reality, there are many important criteria)
- How to determine constraints on other criteria?

Finally (and most importantly), these approaches do not prompt how to determine feasible solution set D with respect to all criteria.

In the present project we consider that the naval design problems are essentially multi-criteria. As a rule, one tries to reduce multi-criteria problems to single-criterion problems. Numerous attempts to construct a generalized criterion in the form of a combination of particular criteria were generally fruitless. By forcing a multi-criteria problem onto the *Procrustean bed* of a single-criterion problem, one replaces the initial problem with a different problem that may have little in common with the original one. As was mentioned in the description of the naval design specific problems, one should always try to take into account all basic performance criteria simultaneously. These criteria are usually contradictory. That is why naval designers experience significant difficulties in formulating the engineering optimization problems correctly. There are many methods of searching for optimal solutions. It is assumed that by using these methods, the user can state an engineering/optimization problem correctly. Unfortunately, this is not the case in reality. Existing optimization methods are not helpful enough in this situation.

Thus, the most important features of naval design optimization problems are following:

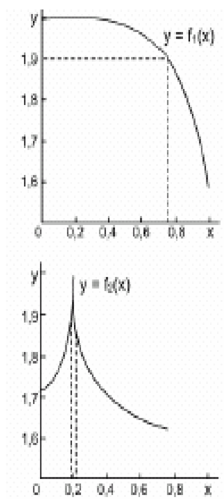
- The problems are essentially multi-criteria ones.
- Determination of the feasible solution set is one of the problem fundamental issues, and construction of this set is an important step in solving such problems.
- The formulation of the problem and its solving is an intertwined process. The feasible solution set may be obtained only in the process of solving; therefore, the problems should be formulated and solved in the interactive mode.

- As a rule, mathematical models are complex systems of equations, including nonlinear differential equations that may be deterministic or stochastic, with distributed or lumped parameters.
- The feasible solution set can be multiply connected, and its volume may be several orders of magnitude smaller than that of the domain limited by variable constrains.
- Both the feasible solution set and the Pareto optimal set are generally non-convex. As a rule, there is no information on smoothness of the goal functions. These functions are usually nonlinear and can be non-differentiable. The dimensionality of design variable and criterion vectors reaches many dozens.

Analysis of the feasible set is important for designers. It allows corrections of the initial boundaries of the design variable ranges and revision of the original objective functions (performance criteria). In particular, this analysis makes it possible to introduce new performance criteria. Designers often do not encounter difficulties in analyzing the feasible solution set and the Pareto optimal set, as well as in selecting the preferred solution. They have a sufficiently well-defined system of preferences.

For manifesting the PSI approach, let us study Multidimensional Parameter Space Using Uniformly Distributed Sequences and Pseudo-Random Number Generators with the following Example of Design Variable Space Criteria: $f_1(x) = 2 - |x - 0.2|^4$ and $f_2(x) = 2 - 0.4331\,|x - 0.2|^{1/4}$.

Here we use 10 uniformly distributed points to investigate design variable space, as shown in Fig. 10. Why are the cubic nets ineffective? Cubic net for two design variables (N=16 points) is shown in Fig. 11, as well as Improved net (LP sequences) for two design variables.



i	x_i	$f_1(x_i)$	$f_2(x_i)$
1	0.05	1.999	1.730
2	0.15	2.000	1.795
3	0.25	2.000	1.795
4	0.35	1.999	1.730
5	0.45	1.996	1.694
6	0.55	1.985	1.667
7	0.65	1.959	1.645
8	0.75	1.908	1.627
9	0.85	1.821	1.611
10	0.95	1.684	1.597

Figure 10: Functions f1 and f2. A table with values of these functions is given in the right part.

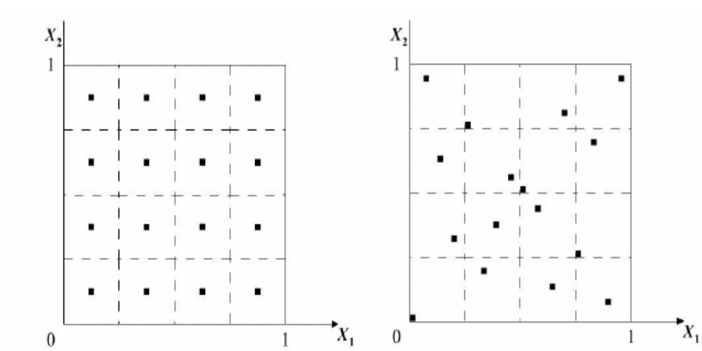


Figure 11: Comparison of different nets in a square

Let us compare two 2D nets shown in Fig.11. In both cases, there are 16 small squares containing a solely net point. So, it may seem that the uniformity of arrangement of points in both nets is equal. However, the situation changes drastically in analyzing a function $f(x_1,x_2)$ that strongly depends on only one argument. Then, calculating the value of the function on the net in the **left square**, one obtains only 4 different values.

On the other hand, calculating f on the net in the **right square**, one obtains 16 different values with much better representation of the whole variation range for the function f. The cubic net turns out to be even worse. For multidimensional cases, the “information loss” in calculating $f(x_1,...,x_n)$ may increase: After calculating $N=M^n$ values of the function $f(x_1)$, we will obtain only $M=N^{1/n}$ different values!

Employing a PSI algorithm, we cover the design variable space with multidimensional points (each point corresponds to the certain design). Thus, we generate many hundreds, thousand, and millions (as necessary) design points in the design variable space. This can be accomplished by distributed sequences and pseudo-random number generators (RNG). Then we compute values of criteria in these points.

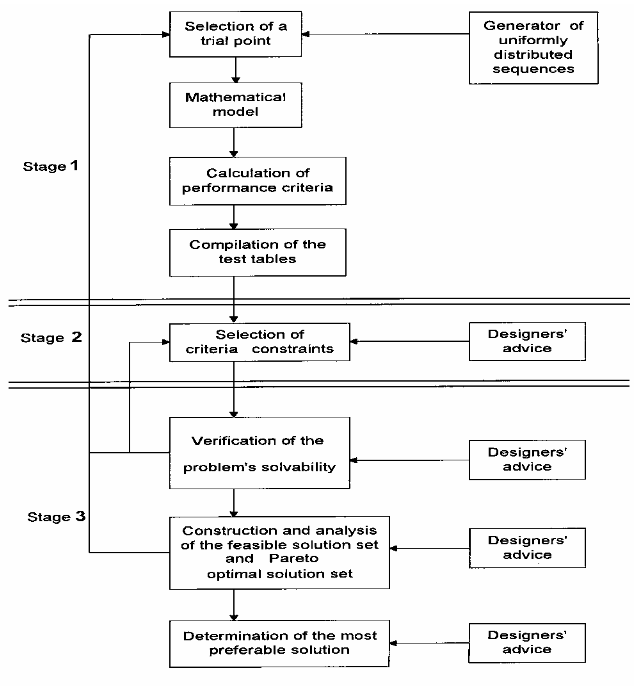


Figure 12: Scheme of PSI algorithm

Analysis of criteria space allows:

- Correct determination of the design variable, functional, and criteria constraints (feasible solution set);
- Construction of Pareto optimal set;
- Selection of the most preferable solution(s) within Pareto set.

Chart of the PSI algorithm in Fig.12 demonstrates the following stages of the algorithm:

Stage 1: Compilation of test tables with the help of a computer;

Stage 2: Selection of criteria constraints;

Stage 3: Verification of the solvability of the problem

Analysis of test tables provides information about relationship between criteria, criterion and design variables, etc. Test table-examples are given in Figs.13 and 14.

An example of investigation of Criteria Space is shown below. As shown in Fig.15, the initial constraints results in the empty feasible set.

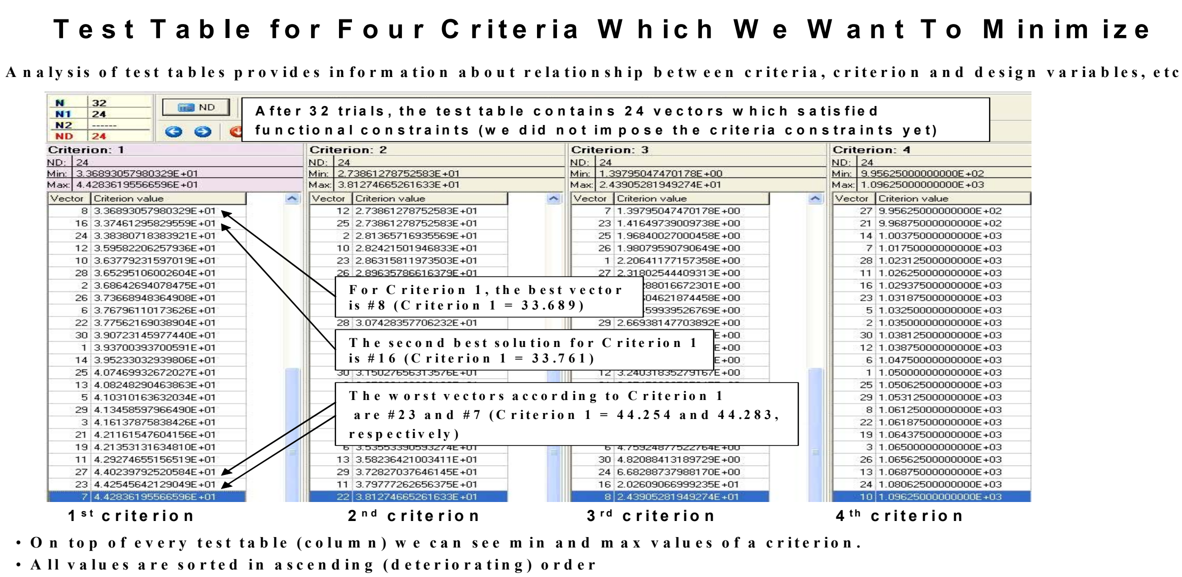


Figure 13: A test table for 4 criteria.

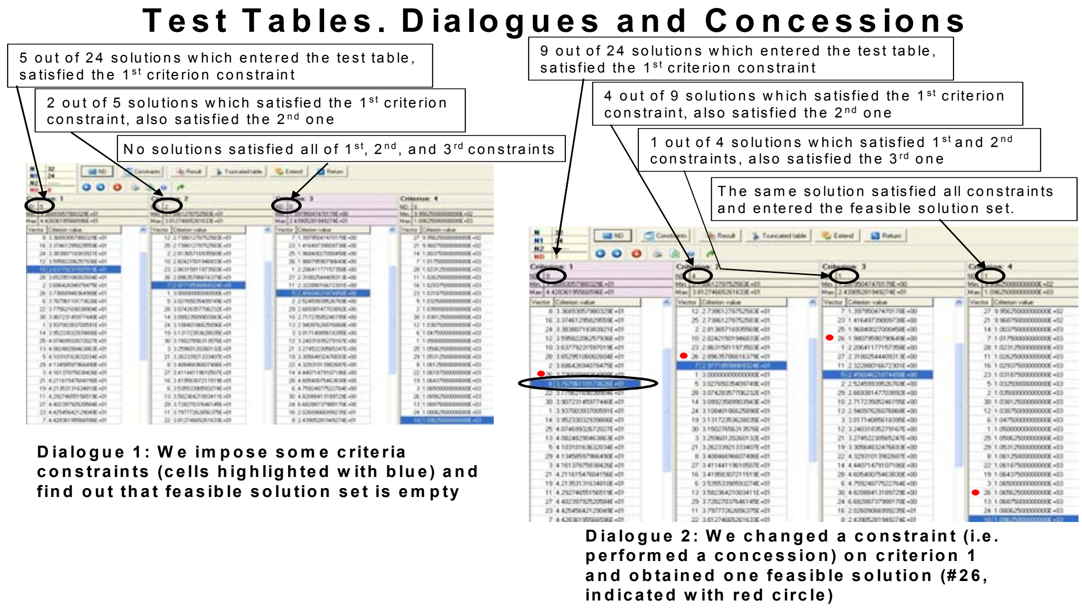


Figure 14: View of screens with dialogues and concessions test table.

The second set of concessions results in a feasible set with 3 solutions in the points 95, 6092, and 1024. We conduct dialogues with computer and obtain a non-empty feasible set. The imposed criteria constraints (30,000, 0.03) were obtained in the last dialogue with computer:

1. The domain of **feasible designs** in the criteria space is designated as Φ(D) and is shown in yellow.
2. All designs in the **feasible domain** Φ(D) can be improved in one or two criteria simultaneously.
3. Design points 306, 16, 6092, 1024; 870 and 1155 belonging to curve Φ(P) are called **Pareto optimal** designs. They cannot be improved in two criteria simultaneously. Improvement in one of these criteria leads to deterioration in the other. There are also examples of computations in the space of design variables in Figs.16, 17, 18 and 19.

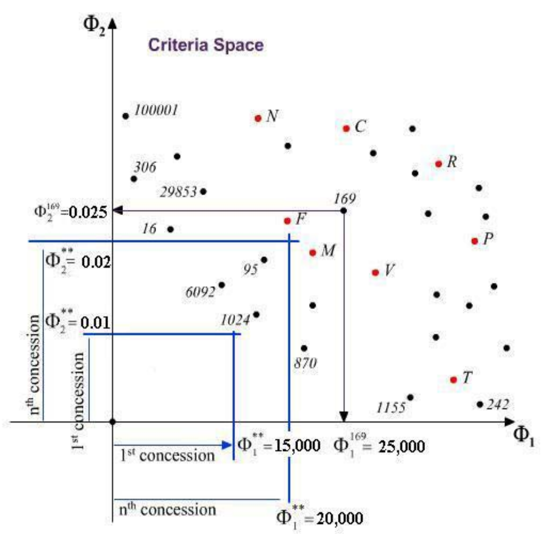


Figure 15: Correction of criterion space

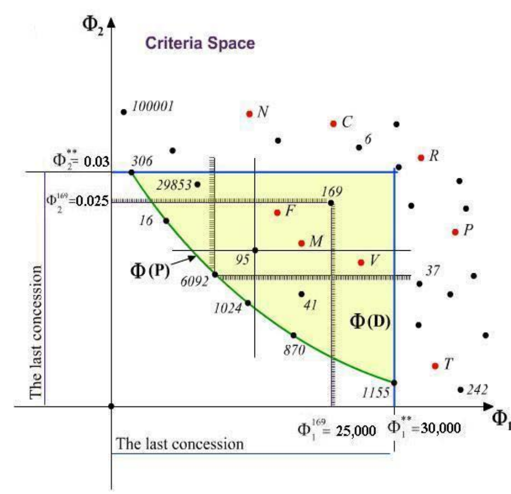


Figure 16: Illustration of Pareto optimal design

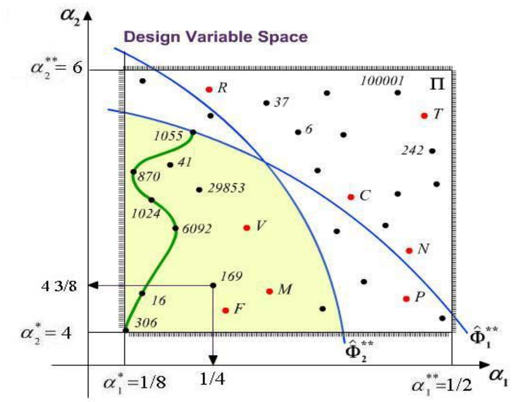


Figure 17: Design variable space without any constraints and with criterion constraints

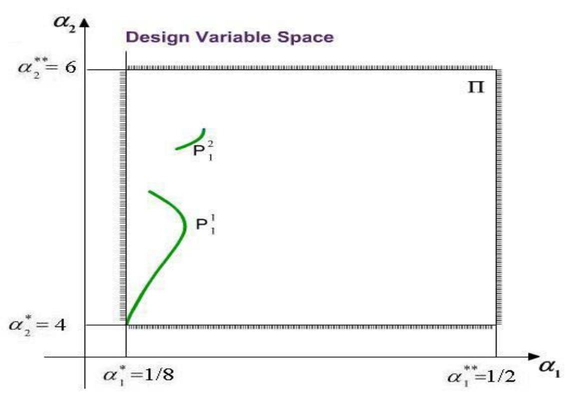


Figure 18: Feasible solution set with functional constraints

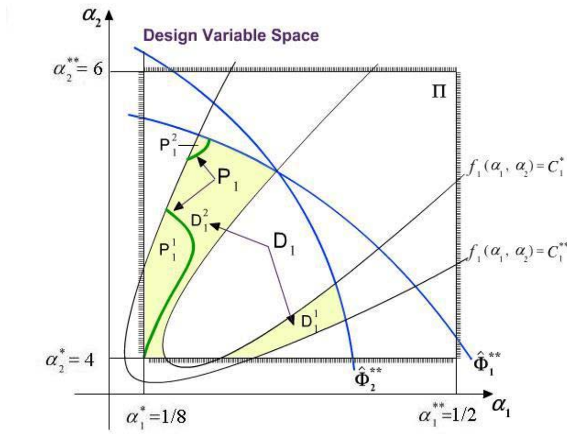


Figure 19: Pareto optimal set

It is possible to deduce a following summary on the PSI approach: In the process of naval design model testing and analysis, it is necessary to obtain information on possibility to correct the constraints. In some cases, the mathematical model will be also corrected. This process should be continued until the designer would be certain that he found a satisfactory solution in the according to his/her system of preferences. This process includes an iterative analysis of the results and correction of the initial statement. This iterative process is indeed the interactive process since the designer plays a crucial role in analyzing the results and making decisions. Investigating the set of Pareto solutions, the designer sees what can be and cannot be achieved. The designer is able to select the most preferable option from the best solutions. Our concessions are something like a market where we have the opportunity to trade until we get what we need.

We can produce designs based on structural optimization of the ship hulls, based on hydrodynamic optimization, and so on. We do not know what the best solutions should be. However, we have to know how Pareto optimal solutions look like. This is a negotiation set, a set of compromises, or a Pareto set. A search for the Pareto set is a necessary condition for optimal design. Trying to do this, we have to know how to construct a sufficiently full feasible set with consideration of all the main performance criteria. As for selecting the most preferable design option in a Pareto set, this falls within the competence of people who make decisions. We must provide the decision-maker with complete information on feasible and Pareto optimal solutions.

Thus, the PSI method makes it possible to:

- ***Define the feasible solution set and Pareto optimal set correctly;***
- ***Determine the dependency of criteria on design variables, the dependency between criteria, significance of the criteria, and expediency of correcting the initial statement of the problems etc.***

5. GENERATION OF COMPUTATIONAL GRIDS AND APPROXIMATIONS

The key issue in any practical optimization is generation of grids (and/or approximations) which can reduce the necessary number of computed variants. The frequently mentioned Response Surface Methodologies (**RSM**) have considered many approaches. Nevertheless, there are basically two absolutely different approaches that can be represented by the polynomial-based "classical" Pruning Algorithm (**PA**) and artificial Neural Networks (**NN**)-based RMS Constructive Algorithm (**CA**).

The specific advantage of the **Neural Network** approaches is in minimization of the necessary grid. A generic optimization loop for NN is shown in Fig. 20. RSM are used in such optimization process primarily in two situations:

1. To replace one or more requested analyses;
2. For design/optimization performed with externally available data, such as experimental measurements

In the first case, the data required for generating the response surface are obtained by performing a number of analyses that is much less than what would be performed in the direct optimization loop. The goal of this study is to develop a MDO tool for ship design, and this goal implies that the optimization task has two primary characteristics:

- It is able to handle a large number of design variables (say up to 100)
- The design space to be completely explored

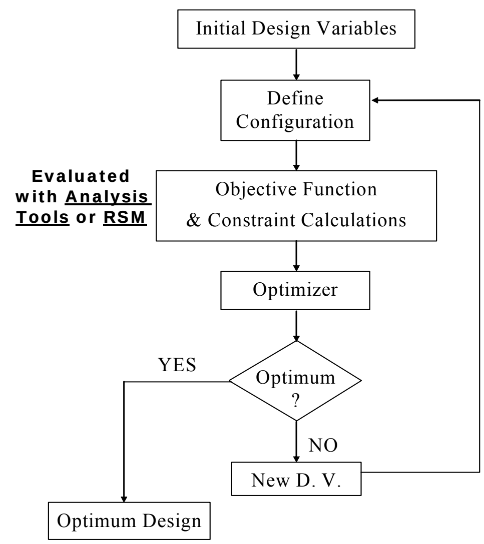


Figure 20: Generic optimization loop

Thus, there are two essentially different approaches for training multi-layer feed-forward networks for function approximation which can lead to variable networks. The pruning algorithms start with a large network, train the network weight until an acceptable solution is found, and then use a pruning method to remove unnecessary units or weights. On the other hand, constructive algorithms start with minimal network, and then grow additional hidden units as needed. Artificial Neural Networks (**ANN**) can be employed for such task and have received considerable attention over the last few years. The types of ANN used for function representation in optimization loops are presented along with a discussion on the selection of the Cascade Algorithm for neural network topology and training method.

Artificial neural networks can be viewed as large multi-input multi-output nonlinear systems composed of many simple nonlinear elements operating in parallel (neurons). The links between neurons are unidirectional and are called connections. Each neuron has multiple inputs and a single output, and its output serves as input to other neurons. A weight factor is assigned to each connection. The network structure or topology is defined by the way neurons are interconnected. Training the network involves estimating the weight of the connections between neurons. Artificial Neural Networks have been used for various applications requiring multiple function analyses. The number of neurons, their activation function and topology of the connections enable the NN to perform its task. For most applications reported to date, however, ANN employed either a fixed topology and/or back propagation for training.

Methods which use a fixed network topology involve an advance (prior to training) evaluation of the type of network that would best suit the application (how many neurons, how many hidden-layers). Since one wishes to develop a general formulation applicable to any problem, one has to rely on a variable network. The advantages of CA versus PA are in the grid/network size. Further, CA requires a small amount of memory because CA usually uses a greedy approach where only part of the weights is trained at once, whereas the other part is kept constant.

A successful learning algorithm for NN is Cascade-Correlation (**CC**) first introduced by Fahlman and Lebiere. Instead of just adjusting the weights in a network of fixed topology, Cascade-Correlation begins with a minimal network, then automatically trains and adds new hidden units one-by-one. This architecture has several advantages over other algorithms: it learns quickly; the network determines its own size and topology; it retains the structure it has built even if the training set changes; and it requires no back-propagation of error signals through the connections of the network. In addition, for a large number of inputs (design variables), back-propagation as the most widely used learning algorithm is very slow. Cascade-Correlation does not exhibit this limitation. Characteristics of the various approaches which can be used as response surface methods are compared in the table in Fig.21.

Pruning algorithm	**Artificial Neural Networks**	
	Training with back-propagation	***Cascade Correlation algorithm***
• Mathematically simple • Requires domain decomposition for nonlinear and non-convex functions • Requires large dataset when design space size increases	• Can satisfactory approximate nonlinear functions • Need to know size *a priori* or end up with too small/large of a network • Training with back-propagation is slow when number of design variables increases	• Can satisfactory approximate nonlinear functions • Network grows to optimum size. • Training is faster for large number of design variables – no back-propagation required

Figure 21: Comparative characteristics of RSM algorithms/approaches

The constructive CC algorithm starts with a minimal network consisting of the input and output layers and no hidden unit (neurons), then automatically trains and adds hidden units until the difference between the targets and the outputs reaches a given small value. It self determines the number of neurons needed as well as their connectivity or weights. The training algorithm involves the following steps:

1. Start with the input (independent variables) and output (dependent variable) that are connected.
2. Train all connections ending at the output unit with a usual learning algorithm until the error E defined by $E = \frac{1}{2}\sum_{p=1}^{P\max}\left\|\mathbf{y_p} - \mathbf{t_p}\right\|^2 = \frac{1}{2}\sum_{p=1}^{P\max}\sum_{i=1}^{m}\left[y_{i,p} - t_{i,p}\right]^2$ keeps decrease. Here m is the number of outputs, Pmax is the size of the training set, $y_{i,p}$ is the ith output from the NN, and $t_{i,p}$ is the target.
3. Generate a pool of candidate units that receive trainable input connections from all of the network's external inputs and from all pre-existing hidden units. The output of each candidate unit is not yet connected to the active network (output). Train each unit (its weights) to maximize the correlation formula C: $C = \sum_{i=1}^{m}\left|\sum_{p=1}^{P\max}\left(z_{0,p} - < z_0 >\right)\left(E_{i,p} - < E_i >\right)\right|$, where z_0 is the output of the candidate hidden unit and $E_{i,p}$ is the residual error of the outputs calculated at Step 2, $E_{i,p}=y_{i,p}-t_{i,p}$. The quantities within brackets <> are averaged quantities over the training set. Training is stopped when C no longer improves. Each candidate unit has a different set of random initial weights. All receive the same input signals and see the same residual error for each training pattern. Because they do not interact with one another or affect the active network, they can be trained simultaneously.
4. Only the candidate with the best correlation score is installed. The other units in the pool are discarded. The best unit is then connected to the outputs and its input weights are frozen. The candidate unit acts now as an additional input unit. Train again the input-outputs connections by minimizing the squared error E as defined in Step 2. Repeat until the stopping criterion is verified.

There are some published examples of NN applications to Naval Design. Particularly, our team members (Schoultz, Hefazi et, al, 2004) have applied NN and CC to hydrodynamic optimization of a hydrofoil for a fast ship, with keeping some constrains of non-hydrodynamic nature. As a result of

employment of NN and CC, the optimization time was reduced from 83 hours (required by direct application of CFD code) to 15.5 hours and the number of variable was reduced down to 28 variables.

NN was proposed for use as part of the PSI approach at the generation of the training sets for the practical large (and complicated) mathematical models of Naval Design System. However, the models/ subsystems like Hydrodynamic Optimization, Structural Optimization contain FEA and CFD codes, which have multiple variables and input information, multiple restrictions and criteria. Some of them relate to numerous performance, mission, and arrangement characteristics. Evaluating the achieved above-mentioned reductions as the certain success, we are, nevertheless, forced to note that:

- 15.5 hours for one-disciplinary optimization is too much to be used in MDO;
- 28 variables of undetermined physical nature is to many for a comprehensive hydrofoil description; for general design problems, it would be sufficient to operate with a set of five variables that includes the hydrofoil maximum chord, its span, its thickness, the zero lift angle of attack and a parameter that describes a spanwise geometry variations (like chord at 5% from the tip).

Summarizing this discussion, we are forced to state that in spite of our preliminary expectations, we cannot consider NN as a promising algorithm for MDO in Naval Design yet.

Pruning Algorithms traditionally employ a polynomial to approximate the desired functions. Although polynomials of any degree may be used, the disadvantages of high degrees for approximation are well known, and the employed degree is usually low. For example, for a quadratic polynomial, the function $y(\boldsymbol{x})$ may be approximated by $y = a_0 + \sum_{i=0}^{n} a_i x_i + \sum_{i=0, j>i}^{n} a_{ij} x_i x_j$, where $x = (x_1, x_2, .., x_n)^T$ and the polynomial coefficients must minimize the difference between data and approximation over the data set. This approximation is frequently accomplished with the least square error method, but there are also other possibilities that can better satisfy either to nature of the data, or to optimization mathematics. Particularly, rejecting gradient calculations, one does not need in continuous derivatives of y. Therefore, a multi-linear approximation $y = \prod_{i=1}^{n} (a_{i0} + x_i a_{i1})$ can be good enough for non-gradient algorithms. There are many different strategies of non-gradient randomized search in the design variable space, depending on the properties of the objective functions. The effort may become unreasonable if quite complex models (such as RANS or FNA solvers) would be involved in the analysis. Hence, a recursive process with a careful selection of the samples to be placed in the design variable space is proposed in the present work. In searching process, we would define a sequence of the trial points in the design space to be analyzed, each one representing a different configuration of the system.

LPτ –sequence will be used in this project. This distribution of trial points displays the best uniformity characteristics and, once the number of the design variables and trial points are defined, can be easily obtained using tabular data. Additionally, a good reconstruction of S and $\boldsymbol{P}$ is finally obtained with higher convergence rate. Let us consider a net consisting of the points $P_1,...,P_N \in K$. To estimate the uniformity of distribution of these points, we introduce the discrepancy $D(P_1,...,P_N)$ between the 'ideal' and actual uniformities. Let P be an arbitrary point of K and G_P be an n-dimensional parallelepiped with the diagonal OP and faces parallel to the coordinate planes. Let us denote by V_{G_P} the volume of G_P and by $S_N(G_P)$ the number of points P_i which enter G_P and whose subscripts satisfy the inequalities $1 \le i \le N$. The discrepancy of the points $P_1,...,P_N$ is the function $D(P_1,\ldots,P_N) = \sup_{P \in K} \left| S_N(G_P) - NV_{G_P} \right|$, where the supremum is taken over all possible positions of the point P within the cube. It is natural to conclude that the smaller $D(P_1,...,P_N)$ is, the more uniformly the points $P_1,...,P_N$ are arranged. Among uniformly distributed sequences known at present, the so-called **LP$_\tau$ sequences** are the best ones as regards

uniformity characteristics as $N \to \infty$. The Cartesian coordinates of a point $Q_i = (q_{i1}, q_{i2}, \ldots, q_{ir})$ are used to calculate the coordinates of a point $a^i = (a_1^i, \ldots, a_r^i)$, $\alpha^i \in \Pi$ from the equation $\alpha_j^i = \alpha_j^* + q_{ij}(\alpha_j^{**} - \alpha_j^*), \quad j = 1, 2, \ldots, r$. Cartesian coordinates of LP sequences are shown in Fig.22 with 16 first 20-dimensional points: $Q_i = (q_{i,1}, \ldots, q_{i,20}), i = 1, \ldots, 16$.

$i=$ 1	0.5	0.5	0.5	0.5	0.5	9	0.5625	0.4375	0.1875	0.8125	0.6875
	0.5	0.5	0.5	0.5	0.5		0.5625	0.9375	0.0625	0.3125	0.1875
	0.5	0.5	0.5	0.5	0.5		0.5625	0.6875	0.9375	0.0625	0.8125
	0.5	0.5	0.5	0.5	0.5		0.3125	0.3125	0.1875	0.6875	0.4375
2	0.25	0.75	0.25	0.75	0.25	10	0.3125	O. 1875	0.9375	0.5625	0.4375
	0.75	0.25	0.75	0.75	0.25		0.8125	0.1875	0.3125	0.0625	0.9375
	0.75	0.25	0.75	0.25	0.75		0.8125	0.4375	0.6875	0.8125	0.5625
	0.25	0.25	0.75	0.25	0.75		0.5625	0.5625	0.4375	0.4375	0.1875
3	0.75	0.25	0.75	0.25	0.75	11	0.8125	0.6875	0.4375	0.0625	0.9375
	0.25	0.75	0.25	0.25	0.75		0.3125	0.6875	0.8125	0.5625	0.4375
	0.25	0.75	0.25	0.75	0.25		0.3125	0.9375	0.1875	0.3125	0.0625
	0.75	0.75	0.25	0.75	0.25		0.0625	0.0625	0.9375	0.9375	0.6875
4	0.125	0.625	0.875	0.875	0.625	12	0.1875	0.3125	0.3125	0.6875	0.5625
	0.125	0.375	0.375	0.875	0.625		0.1875	0.0625	0.9375	0.1875	0.0625
	0.625	0.875	0.875	0.125	0.375		0.6875	0.8125	0.5625	0.6875	0.1875
	0.375	0.875	0.625	0.125	0.125		0.6875	0.1875	0.0625	0.0625	0.8125
5	0.625	0.125	0.375	0.375	0.125	13	0.6875	0.8125	0.8125	0.1875	0.0625
	0.625	0.875	0.875	0.375	0.125		0.6875	0.5625	0.4375	0.6875	0.5625
	0.125	0.375	0.375	0.625	0.875		0.1875	0.312.5	0.0625	0.1875	0.6875
	0.875	0.375	0.125	0.625	0.625		0.1875	0.6875	0.5625	0.5625	0.3125
6	0.375	0.375	0.625	0.125	0.875	14	0.4375	0.5625	0.0625	0.4375	0.8125
	0.875	0.125	0.625	0.125	0.875		0.9375	0.3125	0.1875	0.9375	0.3125
	0.375	0.625	0.125	0.375	0.625		0.4375	0.5625	0.3125	0.9375	0.9375
	0.125	0.625	0.375	0.375	0.875		0.9375	0.4375	0.8125	0.3125	0.0625
7	0.875	0.875	0.125	0.625	0.375	15	0.9375	0.0625	0.5625	0.9375	0.3125
	0.375	0.625	0.125	0.625	0.375		0.4375	0.8125	0.6875	0.4375	0.8125
	0.875	0.125	0.625	0.875	0.125		0.9375	0.0625	0.8125	0.4375	0.4375
	0.625	0.125	0.875	0.875	0.375		0.4375	0.9375	0.3125	0.8125	0.5625
8	0.0625	0.9375	0.6875	0.3125	0.1875	16	0.03125	0.53125	0.40625	0.21875	0.46875
	0.0625	0.4375	0.5625	0.8125	0.6875		0.28125	0.96875	0.28125	0.09375	0.84375
	0.0625	0.1875	0.4375	0.5625	0.3125		0.46875	0.90625	0.65625	0.71875	0.59375
	0.8125	0.8125	0.6875	0.1875	0.9375		0.34375	O.8125	0.21875	0.40625	0.53125

Figure 22: 16 first 20-dimensional points of LP sequences

The values $q_{i,1}, \ldots, q_{i,20}$ are not uniformly distributed between 0 and 1.0, and it is the frequent situation for optimum distributions (For example, the best integration nodes for N=4 are {0.06943184, 0.33000947, 0.66999053, 0.93056816}. These nodes are known as the Gauss nodes). Let us compute a point $\alpha^4 = (\alpha_1^4, \alpha_2^4, \ldots, \alpha_{15}^4)$ using LP$_\tau$ sequences. Say, $5 \le \alpha_1 \le 8$, $10 \le \alpha_2 \le 15, \ldots, 3 \le \alpha_{15} \le 7$. According to table in Fig.22, $Q_{4,15} = (q_{4,1}, q_{4,2}, \ldots, q_{4,15}) = (0.125;\ 0.625; \ldots; 0.375)$. Thus, $\alpha_j^i = \alpha_j^* + q_{ij}(\alpha_j^{**} - \alpha_j^*)$, $\alpha_1^4 = 5 + 0.125(8-5) = 5.375$, $\alpha_2^4 = 10 + 0.625(15-10) = 13.125$, …, $\alpha_{15}^4 = 3 + 0.375(7-3) = 4.5$. Two projections of the 50-dimensional LP Sequences onto the plane of two design variables are shown in Fig.23. Let us also remind that accuracy of approximation of functions also depends on distributions/sequences of the points.

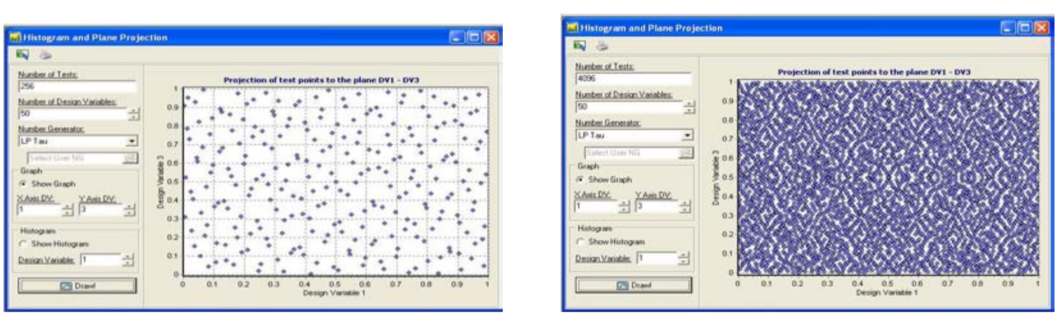


Figure 23: Examples of projection of 50-dimensional LP Sequences in a plane. Left screen corresponds to N=256, right screen corresponds to N=4096

An example of approximation of physical solutions on a rare grid and its following use in a naval design problem is given below. This problem relates to torpedo design. Some of contemporary torpedoes hunt a target ship by following her wake. Because the air bubble concentration in the ship wake is higher than in surrounding water, this wake can be determined by acoustical detecting of the concentration gradient. Such guidance/targeting requires first a frequent trespassing the wake (that can be performed at a zigzag trajectory, with periodical turns at the drift angles α≈3-4 degrees) and second low ultrasound radiation by torpedo itself. Because the main source of such radiation is cavitation inception, it must be suppressed absolutely. There is a parameter σ that describes possibility of this inception. For the two-meter submergence $\sigma = 230/(0.515V_s)^2$, where V_S is the torpedo speed in knots. For V_S=55 inherent to maximum speed of the Raytheon torpedo MK48, σ=0.285 (and it would be 0.345 for V_S=50). The cavitation inception may occur where the dimensionless pressure coefficient Cp decreases down to –σ. This coefficient depends on the shape of the torpedo head (illustrated by Fig.25), and determination (and optimization) of its dependency on shape parameters is a physical problem.

On the other hand, the guidance/targeting is manufactured as a truncated cone of revolution of fixed sized and the displacement problem is put it in the torpedo hull taking into account the necessity to keep the overall dimension of the torpedo (its caliber D_T, etc). Thus, there is a quite simple but multi-disciplinary design problem.

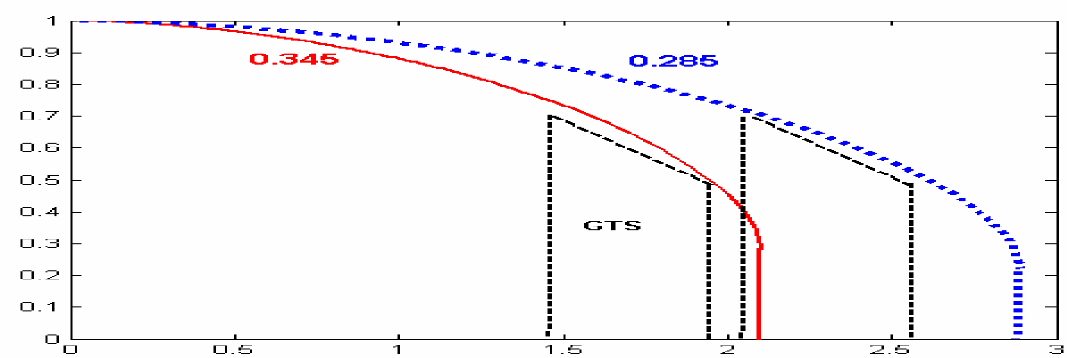


Figure 25: Meridian sections of torpedo heads with inserted box of guidance/targeting system (GTS). All lengths are related to a half of the caliber. The box in feasible positions is limited by dashed segments. Numbers near hull sections show design values of σ, design angle is 4 degrees.

The shape of torpedo head with maximum volume in the given ranges of σ and α can be described as:

$$Y(x) = \frac{D_T}{2}\left[R_1 + (1-R_1)(1-(xR_2)^{R_3}\right]^{R_4}.$$

The dependencies of $R_1,\ldots,R_4$ on σ and α are obtained by solving a nonlinear problem (Amromin & Boushkovskii, 1997) with unique computer codes. The results are following: $R_3 = 10/(5.2+\sqrt{\sigma - 0.15})$, $R_4 = 0.57 + 0.03(\sigma - 0.1)$, the coefficients R_1 and R_2 can be approximated by bilinear functions with employment of the data set from the Fig.26.

α°	σ	R_1	R_2
0	0.2	0.285	0.28
4	0.2	0.12	0.18
0	0.3	0.38	0.53
4	0.3	0.24	0.375
0	0.41	0.48	0.81
4	0.41	0.333	0.61

Figure 26: Optimum sizes of torpedo head versus α and σ

One can see in Fig.25 that there is a general possibility to insert the GTS box within head assigned to the 55-knots speed, but there is also constrain for the head length (less than D_T±5% of D_T), and the 50-knots variant only becomes feasible with 4-degree turns.

6. Simplified Examples of Multi-Disciplinary Naval Design

Bulk Carrier Design Optimization Model: A six-parameter, three-criterion example MDO with 14 or 16-constraints is presented to illustrate the use of PSI method here. This model relates to a family of bulk carriers with deadweight between 3,000 and 500,000 tons and speeds between 14 and 18 knots. This is a simplified synthesis parametric commercial ship sizing problem in which the design parameter vector is x = $\{L, B, D, T, C_B, V_k\}$. Here L is length, B is beam, D is depth, T is draft (all in meters), C_B is block coefficient and V_k is the ship speed (in knots). There are three optimization criteria:

$$\min f_1(x) = \text{transportation cost} \equiv \text{annual costs/annual cargo}$$

$$\min f_2(x) = \text{light ship weight} \equiv W_s + W_o + W_m$$

$$\max f_3(x) = \text{annual cargo capacity} \equiv \text{cargo DWT} \cdot \text{RTPY}$$

Here steel weight $W_s = 0.034L^{1.7}B^{0.7}D^{0.4}C_B^{0.5}$, outfit weight $W_o = 1.0L^{0.8}B^{0.6}D^{0.3}C_B^{0.1}$, machinery weight $W_m = 0.17P^{0.9}$, P is power, displacement M=$1.025LBTC_B$, Froude number $F_n = V/(gL)^{0.5}$, $V=0.514V_k$m/s, g=9.81m/s^2, RTPY means round trips per year, DWT is deadweight. As stated, the criteria 2 and 3 are in obvious direct conflict. Such example was also considered by Sen & Yang (1998), but their problem formulation includes 13 following constraints:

$L/B \geq 6$	$3{,}000 \leq \text{DWT}$	$14 \leq V_k$
$L/D \leq 15$	$\text{DWT} \leq 500{,}000$	$V_k \leq 18$
$L/T \leq 19$	$0.63 \leq C_B$	$F_n \leq 0.32$
$T \leq 0.45\text{DWT}^{0.31}$	$C_B \leq 0.75$	$KB + BM_T - KG \geq 0.07B$
$T \leq 0.7D + 0.7$		

Here vertical center of buoyancy $KB = 0.53T$, metacentric radius $BM_T = (0.085C_B - 0.002)B^2/(TC_B)$, vertical center of gravity $KG = 1.0 + 0.52D$. Here two different problems will be presented using two additional constraint sets to provide more realistic problems than that are in the mentioned book. Besides of thirteen above constraints, the first problem includes an additional constrain that reflect the dock 900-feet limit:

$$L \leq 274.32$$

The second problem includes also fifteen and sixteen constrains on ability to move by Panama channel and SW:

$$B \leq 32.31 \qquad T \leq 11.71$$

The approximate model uses the Admiralty coefficient method for the power estimation. Therefore,

$$P = M^{2/3}V_k^3/(a + bF_n)$$

Here $a = 4{,}977.06C_B^2 - 8{,}105.61C_B + 4{,}456.51$, $b = -10{,}847.2C_B^2 + 12{,}817C_B - 6{,}960.32$. It is supposed that annual cost is the sum of capital costs, running costs and voyage costs, where:

Capital costs=0.2*ship cost
Ship cost =1300($2W_s^{0.85} + 3.5W_o + 2.4P^{0.8}$)
Running costs = 40,000 DWT$^{0.3}$;
Voyage costs = (fuel cost + port cost) · RTPA;
RTPA= 350/(sea days + port days);
Fuel cost=1.05 daily consumption · sea days · fuel price;
Cargo DWT = DWT – fuel carried – miscellaneous DWT;
Fuel carried = daily consumption · (sea days + 5);
Port days = 2[(cargo DWT/handling rate) + 0.5];
Daily consumption = 0.19 P · 0.024 + 0.2;
Port cost = 6.3 DWT$^{0.8}$;
Fuel price=100 £/t;
Round trip miles = 5,000;
Sea days = round trip miles/24V_k ;
DWT = M – (**$W_s + W_o + W_m$**);
Miscellaneous DWT = 2.0DWT$^{0.5}$;
Handling rate = 8,000 (t/day);

Thus, there is a three-criterion problem shown in Fig.26. Six selected variables are also given there.

Criterion #1	**transportation cost (£/t)**
Criterion #2	**light ship weight (t)**
Criterion #3	**annual cargo (t)**
Variable # 1	**length (m) *L***
Variable # 2	**beam (m) *B***
Variable # 3	**depth (m) *D***
Variable # 4	**draft (m) *T***
Variable # 5	**block coefficient C_B**
Variable # 6	**speed (knots) V_k**

Figure 26: Criteria and variables in Sen & Yang problem

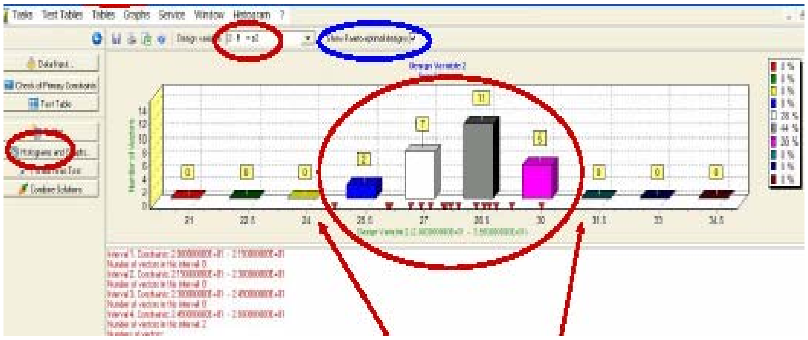
We applied PSI to this model and showed the PSI results. We can use this model as a template for future marine design problems

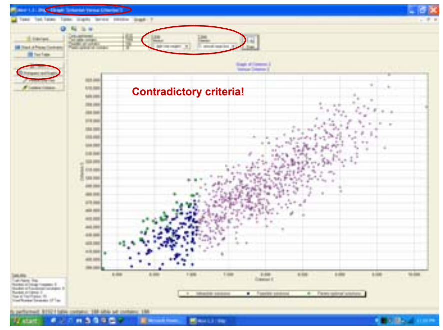
For this sample model, 8192 tests were conducted, but only 146 vectors entered the test table because 8046 vectors did not satisfy the functional constraints. The Pareto set for this model is given in Fig. 27. Some screen fragments reflecting the solving procedure are illustrated Fig. 28.

Tests performed 8192
Feasible set contains: 146
Pareto-optimal set contains: 39

	# of vector	Criterion #1	Criterion #2	Criterion #3	Variable # 1	Variable # 2	Variable # 3	Variable # 4	Variable # 5	Variable # 6
1	226	9.716	6,850.201	456,667.225	169.525	26.607	15.441	10.546	0.748	15.109
2	290	9.879	7,053.307	497,836.591	169.190	28.116	14.807	10.909	0.730	16.195
3	1396	9.999	6,595.151	448,699.343	166.255	27.226	15.273	10.470	0.701	15.979
4	1434	8.991	6,857.799	465,302.255	172.024	27.021	14.746	10.948	0.749	14.150
5	1596	9.385	6,385.747	434,211.463	168.100	27.409	13.598	10.200	0.717	14.701
6	1696	9.388	6,092.592	417,649.865	160.721	26.443	15.063	10.487	0.734	14.217
7	2028	10.973	6,588.573	451,560.426	167.496	25.227	14.702	10.384	0.742	16.740
8	2122	9.063	7,004.999	478,456.093	171.009	27.133	15.689	11.239	0.747	14.470
9	2412	10.419	6,353.191	447,361.550	167.320	26.064	14.039	10.481	0.696	16.790
10	2508	9.192	6,674.035	440,565.528	166.917	27.441	15.777	10.686	0.726	14.118
11	2544	10.585	6,407.315	449,989.819	162.088	26.855	14.293	10.194	0.739	16.306
12	2596	11.248	6,634.859	457,687.349	164.872	26.701	14.874	10.327	0.706	17.513
13	2762	10.283	6,941.009	469,163.925	171.177	26.496	15.245	10.614	0.724	16.372
14	2826	9.779	6,983.067	467,127.089	170.842	27.770	14.630	10.306	0.739	15.442
15	2950	9.485	6,659.746	449,692.978	173.122	25.397	14.493	10.703	0.748	14.833
16	3208	11.514	6,775.663	480,260.359	162.306	26.792	14.998	10.646	0.742	17.456
17	3304	9.558	5,811.754	389,281.878	163.111	25.679	13.397	9.853	0.732	14.050
18	3322	10.112	7,030.911	478,717.811	172.770	27.320	14.178	10.400	0.735	16.175
19	3384	10.249	6,317.658	425,346.986	163.849	26.953	14.832	10.052	0.697	16.011
20	3932	10.370	6,803.807	470,215.857	167.907	26.873	15.413	10.746	0.707	16.726
21	4118	10.305	6,756.733	461,030.318	173.956	26.828	14.424	10.588	0.660	17.286
22	4304	10.051	6,037.302	420,241.556	161.480	26.506	13.662	9.945	0.731	15.395
23	4370	9.666	6,406.107	438,001.225	169.731	25.876	14.258	10.526	0.716	15.293
24	4604	9.289	6,516.606	444,965.250	168.523	26.140	15.137	10.896	0.729	14.590
25	4844	9.106	6,333.252	425,740.630	167.416	27.788	14.751	10.701	0.667	14.461
26	5144	9.731	6,087.257	421,903.012	163.241	26.348	14.212	10.299	0.713	15.163
27	5226	9.014	6,867.039	465,880.176	171.558	27.696	14.954	10.983	0.720	14.444
28	5294	9.264	6,968.857	467,052.253	175.717	28.077	14.505	10.778	0.679	15.366
29	5698	9.277	7,074.518	480,937.191	168.909	27.835	15.896	10.993	0.749	14.760
30	6092	9.556	6,484.338	447,577.425	166.964	27.205	13.699	10.220	0.748	14.893
31	6594	10.335	6,621.257	449,088.708	169.068	27.222	13.602	9.921	0.723	16.216
32	6608	9.384	5,836.636	408,006.455	161.555	25.112	14.071	10.467	0.749	14.091
33	6718	9.082	6,753.588	429,399.994	176.681	27.185	14.389	10.546	0.684	14.041
34	6970	9.835	6,644.216	453,834.958	172.456	26.233	14.555	10.690	0.695	16.033
35	7252	10.854	6,328.252	433,516.212	165.664	26.661	13.463	9.786	0.709	16.820
36	7292	9.463	6,317.147	423,913.539	168.347	27.013	14.635	10.496	0.670	15.132
37	7814	9.759	6,801.131	456,191.395	173.076	27.958	14.308	10.384	0.673	16.121
38	7852	10.609	6,963.664	497,673.935	167.173	27.606	14.386	10.767	0.739	16.933
39	7988	9.240	6,226.486	419,298.601	166.033	27.650	14.122	10.336	0.687	14.410
	Min	**8.991**	**5,811.754**	**389,281.878**	**160.721**	**25.112**	**13.397**	**9.786**	**0.660**	**14.041**
	Max	**11.514**	**7,074.518**	**497,836.591**	**176.681**	**28.116**	**15.896**	**11.239**	**0.749**	**17.513**

Figure 27: Pareto Optimal Set for the Bulk Carrier Design Optimization Model.





Redefinition of the bounds for B

Figure 28: Illustrations to solving modified Sen & Yang problem. On the bottom plot, the right part of the square in the plan $\{f_3,f_2\}$ is covered by infeasible solutions.

The results shown in Fig.27 were obtained with one optimization method (min-max design). Another optimization method generally gives another solution. One can see in Fig. 29 the effects of both selection of mathematical technique and the weight selection within a solely technique.

OPTIMIZATION METHOD	Criterion #1	Criterion #2	Criterion #3	Variable # 1	Variable # 2	Variable # 3	Variable # 4	Variable # 5	Variable # 6
Weighted Sum Design ($w_1=w_2=w_3$)	9.474	5,240.300	386,500.000	150.730	25.120	13.840	10.390	0.750	14.000
Min - Max Design	11.514	7,709.600	549,557.000	169.070	28.180	15.360	11.450	0.750	18.000
Nearest to the Utopian Design	8.953	6,290.900	452,018.000	161.960	26.990	14.870	11.110	0.750	14.050
Weighted Sum Design ($w_1=w_3=0.4$, $w_2=0.2$)	8.742	6,808.000	480,947.000	167.120	27.850	15.350	11.440	0.750	14.000
Weighted Sum Design ($w_2=w_3=0.2$, $w_1=0.6$)	8.814	6,566.500	462,985.000	165.690	27.620	15.060	11.240	0.736	14.000
Weighted Sum Design ($w_1=w_2=0.2$, $w_3=0.6$)	8.626	7,179.500	501,210.000	170.640	28.440	15.670	11.670	0.750	14.000
Weighted min-max ($w_2=w_3=0.6$, $w_1=1.8$)	9.281	7,379.300	527,783.000	170.720	28.450	15.630	11.640	0.750	15.500
Weighted min-max ($w_1=w_3=0.6$, $w_2=1.8$)	9.116	6,274.400	424,010.000	168.840	28.100	14.190	10.630	0.643	14.790
Weighted min-max ($w_1=w_2=0.6$, $w_3=1.8$)	10.332	10,529.900	689,587.000	192.340	32.060	17.490	12.950	0.750	18.000
Goal Programming ($w_1=w_2=w_3=1/3$)	9.474	5,240.300	386,500.000	150.730	25.120	13.840	10.390	0.750	14.000
Goal Programming ($w_1=0.6$, $w_2=w_3=0.2$)	8.826	6,535.200	461,666.000	165.290	27.550	15.040	11.230	0.738	14.000
Goal Programming ($w_1=w_2=0.2$, $w_3=0.6$)	8.626	7,179.500	501,209.000	170.640	28.440	15.670	11.670	0.750	14.000

Figure 29: Effect of selection of an optimization method on the design results

MIT Surface Combatant Design Synthesis Model: The model for Naval Ship design optimization example is the adapted MATLAB version of the MIT Functional Ship Design Synthesis Model, which was initially written in MATHCAD. It was a modified version of the Axiomatic Design Model created by John Szatkowski (2000). Several assumptions were made during the MATLAB modification of the initial model for optimization and a very simplified cost model (lead-ship end cost only) is added using the former version of the MIT Functional Ship Design Synthesis Model. This ensured a reasonable estimate of the cost with respect to the different designs.

The MIT Functional Ship Design Synthesis Model is a concept level design model for monohull surface combatants. This model is used in the 13.412 Principles of Naval Ship Design course offered at Massachusetts Institute of Technology. The model was originated as a master thesis by M. R. Reed

(1976) and has been modified by naval officers and MIT faculty for more than twenty years. Two earlier codes, the Navy's destroyer design model, DD07 and the Center of Naval Analyses Conceptual Design of Ships Model (CODESHIP), are used as its basis. The recent version has regression-based equations for weight, area, and electric power which are more consistent with the Naval Surface Warfare Center's Advanced Surface Ship Evaluation Tool (ASSET). Information on employed systems is given in Fig.30.

SYSTEM DESCRIPTION	WT KEY
NAVIGATION EQUIPMENT	
NAVIGATION SYSTEM	W420
SENSORS	
IFF	W455
MULTIPLE MODE/FUNCTION RADAR	W456
TOWED TORPEDO ALERTMENT ARRAY	W462
BOW SONAR	W463
ELECTRONIC WARFARE SENSORS	W466
ELECTRO OPTIC SENSOR	W466
WEAPONS SYSTEMS	
MISSILE WEAPON CONTROL SYSTEM	W482
INTEGRATED FIRE CONTROL SYSTEMS	W484
GUN	W711
AMMUNITION HANDLING	W712
AMMUNTION STOWAGE - READY SERVICE AND MAGAZINES	W713
LAUNCHING SYSTEMS, MISSILE (MK 48 Mod 2 - 8 Cells)	W721
TORPEDO TUBES ON DECK	W750
SURFACE TO SURFACE MISSILE LAUNCHER (Mk 140 LtWt - 2 Quad Launchers)	W721
MISSILES - 32 ESSM	WF21
AMMO - 300 Rounds	WF21
LIGHTWEIGHT ASW TORPEDOES - 6	WF21
SURFACE TO SURFACE MISSILES - 8	WF21
NETWORK SYSTEMS	
CIC ELEX	W411
EXCOMM + MINI CEC	W440
EMBARKED AIRCRAFT - AUTONOMOUS/REMOTE OPERATED VECHICLES	
Minehunting AUV/Remote Minehunting System	W478
UAV, Operating System	W495
LAMPS Mk III Fuel System	W542
LAMPS Mk III RAST System/Helo Control	W588
LAMPS Mk III Aviation Shop, Office	W665
LAMPS Mk III Torpedos (Mk 46 x 18), Sonobuoys and Pyrotechnics	WF22
LAMPS Mk III SH60 Helicopter and Hangar	WF23
LAMPS Mk III Aviation Support and Spares	WF26
LAMPS Mk III Fuel	WF42
COUNTERMEASURES	
PASSIVE ECM	W472
TORPEDO DECOY	W473
TORPEDO COUNTERMEASURES	W474
COUNTERMEASURES/DECOY STOWAGE	W763
COUNTERMEASURES/DECOY CANNISTERS - 100 RDS	WF21
PAYLOAD SUPPORT/AUX SYSTEMS	
RADAR - COOLING SYSTEM	W532
VLS AUXILIARY EQUIPMENT	W555
PAYLOAD OUTFIT ITEMS	
VLS ARMOR - LEVEL III HY-80	W164
GUN HY-80 ARMOR LEVEL II	W164
MISC SYSTEMS	
20mm STOWAGE	W763
20mm AMMUNITION - 8000 rounds	WF21

Figure 30: Information on systems of a designed surface combatant

There are forty five design parameters in this model. Sixteen of them are discrete variables. The first eight of these parameters are the basic design parameters. These parameters are listed in Fig.31.

Number	Symbol	Title	Comments
1	LWL	Length (ft)	
2	B	Beam (ft)	
3	Ndesks	Number of Hull Decks	DISCRETE (2 ,3, 4)
4	CP	Prismatic Coefficient.	$0.54<CP<0.64$
5	CX	Maximum Section Coefficient	$0.7<CX<0.85$
6	HDKh	Average Hull Deck Height (ft)	
7	BILGE	Bilge Height (ft)	
8	HDKd	Average Deckhouse Deck Heigh (ft)	
9	NPENG	Number of Propulsion Engines	DISCRETE (1, 2, 3, 4)
10	eta	Propulsor Mechanical Efficiency	
11	NDIE	Deckhouse decks impacted by propulsion & generator	DISCRETE (1, 2)
12	NHPIE	Hull decks impacted by propulsion inlet/exhaust	DISCRETE (1, 2, 3, 4)
13	WF46	Lubrication Oil weight (lton)	
14	NP	Number of propellers.	DISCRETE (1, 2)
15	DP	Propeller diameter (ft)	
16	LS	Shaft length (ft)	
17	ADB	Bridge area (ft^2)	
18	WIC	Gyro/IC/Navigation Weight (W420,W430) (lton)	
19	Nfins	Number of Fin Stabilizer Pairs.	DISCRETE (0, 1)
20	CSD	Drag Coefficient	
21	ASD	Sonar Area (ft^2).	DISCRETE (SQS56=27; SQS53C=215)
22	W498	Sonar Dome Water Weight (lton)	
23	VCG498	Sonar Dome Water Vertical Center of Gravity (ft)	
24	ACOXO	Living Area for CO and XO (ft^2)	
25	vf	Volume factor.	DISCRETE (FFG7=3.5, DDG51=5.2)
26	CDHMAT	Deckhouse material.	DISCRETE (Aluminum=1, Steel=2)
27	CPS	Collective Protection System. DISCRETE (0, 1)	DISCRETE (0, 1)
28	kWM	Miscellaneous (kW)	
29	W593	Environmental Support Systems Weight (lton)	
30	W171	Mast Weight (lton)	
31	VWASTE	Waste Oil Volume (ft^3)	
32	W598	Aux Systems Operating Fluid Weight (lton)	
33	NG	Number of generators	DISCRETE (2, 3, 4)
34	NHeIE	Hull decks impacted by generator inlet/exhaust	DISCRETE (1, 2, 3, 4)
35	WBP	Burnable propulsion endurance fuel weight (lton)	
36	D10C	Constant for Depth at Station 10, D10xC	
37	FP	Payload Weight Fraction	
38	WOFH	Hull Fittings (lton)	
39	CHMAT	Hull Material	DISCRETE (0.93, 1.00)
40	CBVC	Clean Ballast Volume Constant	DISCRETE (0, 1)
41	LCB	The LCB from middle ships as percent of length	Minus to aft
42	PMF	Power Margin Factor	margin for concept design = 10%
43	PC	Approximate Propulsive Coefficient	
44	SELECTP	Selection of propulsion engines	DISCRETE (1, 2, 3, 4, 5, 6, 7)
45	SELECTG	Selection of generators	DISCRETE (1, 2, 3, 4, 5, 6, 7)

Figure 31: Design parameters of MIT surface combatant model

For the parameters number 44 and 45, discrete values of variables correspond to different models of propulsion engines and generators. The parameters of these devices are given in Fig. 32.

SELECTG	Model	Weight (lton)	Length (ft)	Width (ft)	Height (ft)	Power (hp)	SFC (lbm/hp-hr)	Inlet X-sect (ft^2)	Exhaust X-sect (ft^2)
1	CAT 3608 IL8	18.70	15.80	5.74	8.62	3390	0.3100	0.00	2.40
2	GM 16-645E5	16.80	17.64	5.64	9.25	3070	0.3800	0.00	2.20
3	Other (LSD 41)	11.40	15.18	6.46	9.79	2100	0.3700	0.00	2.10
4	F 38TD8-1/8-12	21.80	30.10	7.00	7.00	3500	0.3300	0.00	3.00
5	DDA 501-K34	0.60	7.50	2.80	2.60	4600	0.4730	24.00	11.70
6	DDA 570-KA	0.60	6.00	2.63	2.58	5965	0.4763	23.90	11.60
7	GE LM 500	0.57	7.20	2.80	2.80	4500	0.4812	20.90	10.20

SELECTP	Type/Model	Weight (lton)	Length (ft)	Width (ft)	Height (ft)	Power (hp)	SFC (lbm/hp-hr)	Inlet X-sect (ft^2)	Exhaust X-sect (ft^2)
1	Diesel/PC 4.2V10	189.30	34.20	17.00	24.50	16270	0.3130	34.50	15.10
2	Diesel/F/PC2/16-DD	79.60	28.00	12.15	12.76	10400	0.3400	21.70	9.70
3	Diesel/PC 4.2V14	257.14	38.30	17.25	22.20	22778	0.3100	46.20	22.30
4	Diesel/PC 4.2V18	312.50	44.80	17.25	22.20	29286	0.3100	59.40	28.70
5	Gas Turbine/GE LM2500-30	3.10	15.65	5.20	5.20	26250	0.3930	99.60	51.00
6	Gas Turbine/Other (DDG 51)	3.10	15.65	5.20	5.20	25775	0.4100	106.00	53.10
7	Gas Turbine/GE LM5000	4.80	19.67	6.50	6.50	39100	0.3868	159.30	79.00

Figure 32: Parameters of generators and propulsion engines for a surface combatant

There are six following criteria in this problem:

$$\min\{ERRKW=100\times(kWG/kWGREQ-1)\}$$
$$\min\{ERRPOWER=100\times(PI / PIREQ-1)\}$$
$$\max\{ERRVOL=100\times(VTA/VTR-1)\}$$
$$\max\{ERRAREA=100\times (ATA/ATR-1)\}$$
$$\max\{ERRWEIGHT=100\times(DELTAFL/ WT-1)\}$$
$$\min\{COST\}$$

Here kWG=Generator power (each generator) (kW); kWGREQ= Installed Electrical Power required per generator (kW); PI= Total Shaft Horsepower; PIREQ=Installed Shaft Horsepower required to achieve sustained speed; VTR=Total Required Volume (ft^3); VTA=Total Actual Volume (ft^3); ATR=Total Required Area (ft^2); ATA=Total Actual Area (ft^2); WT=Total Weight (lton); DELTAFL=Full Load Displacement (equal to full load weight) (lton).

There are also eleven functions:

f1= kWG – kWGREQ
f2= D10x – D10SL
f3= GM;
f4 = PI – PIREQ
f5= Eact – E
f6= Ndecks – NHPIE
f7= Ndecks – NHeIE
f8= CLB
f9= CBT
f10= CDELTAL
f11=CGMB

These functions are subject to sixteen different functional constraints, but only seven of them are rigid, whereas nine other are soft and can be considered as pseudo-criteria:

f1= kWG – kWGREQ≥ 0
f2= D10x – D10SL≥ 0
f3= GM> 0
f4= PI – PIREQ≥ 0
f5= Eact – E≥ 0
f6= Ndecks – NHPIE≥ 0
f7= Ndecks – NHeIE≥ 0

f5 = Eact – E	Pseudo-criterion (MIN)
f8 = CLB ≤10	Pseudo-criterion (MIN)
f8 = CLB≥ 7.5	Pseudo-criterion (MAX)
f9 = CBT≤ 3.7	Pseudo-criterion (MIN)
f9 = CBT≥ 2.8	Pseudo-criterion (MAX)
f10= CDELTAL ≤ 65	Pseudo-criterion (MIN)
f10= CDELTAL ≥ 45	Pseudo-criterion (MAX)
f11= CGMB≤ 0.122	Pseudo-criterion (MIN)
f11= CGMB≥ 0.09	Pseudo-criterion (MAX)

Here E= Range (mile) (Design requirement); Eact= Range (mile) (Actual); CLB= Length to Beam Ratio; CBT= Beam to Draft Ratio; CDELTAL= Displacement to Length Ratio (lton/ft^3); CGMB=Transverse dynamic stability (GM/B). It is essentially that ERRKW, ERRPOWER, ERRVOL, ERRAREA, ERRWEIGHT must be equal or greater than zero.

The initial approach (prototype) of ship is described by Fig.33. The functional constraints "f1≥0" and "f4≥0" ensure ERRKW, and ERRPOWER to be equal or greater than zero respectively. These values might be very large, hence they were first minimized, and then some reasonable maximum values were selected as criterion constraints. However, small percentage of negative values is acceptable for ERRVOL, ERRAREA, and ERRWEIGHT. Therefore, they were first maximized, and then reasonable values were selected as criterion constraints. The sixth criteria, COST, were always minimized.

A Visual C++ code is written and compiled for the MATLAB model to interface with MOVI SOFTWARE. After each optimization step, the design variable histograms and the design variable tables were used to pick new values for the design variable constraints to improve the results. The stiffness of pseudo-criteria constraints was increased after each optimization step as well.

Values of vectors:	
1 - LWL (p1)	356.2500
2 - B (p2)	39.3750
3 - Ndecks (p3) DISCRETE	2
4 - CP (p4)	0.6213
5 - CX (p5)	0.8031
6 - HDKh (p6)	8.5000
7 - BILGE (p7)	5.0000
8 - HDKd (p8)	8.0500
9 - NPENG (p9) DISCRETE	2
10 - eta (p10)	0.9700
11 - NDIE (p11) DISCRETE	2
12 - NHPIE (p12) DISCRETE	1
13 - WF46 (p13)	17.6000
14 - NP (p14) DISCRETE	1
15 - DP (p15)	12.0000
16 - LS (p16)	100.5000
17 - ADB (p17)	538.9000
18 - WIC: (p18)	43.8000
19 - Nfins (p19) DISCRETE	0
20 - CSD (p20)	0.2800
21 - ASD (p21) DISCRETE	27
22 - W498 (p22)	14.2000
23 - VCG498 (p23)	-3.0000
24 - ACOXO (p24)	325.0000
25 - vf (p25) DISCRETE	3.5
26 - CDHMAT (p26) DISCRETE	2
27 - CPS (p27) DISCRETE	1
28 - kWM (p28)	46.1000
29 - W593 (p29)	14.7000
30 - W171 (p30)	2.0000
31 - VWASTE (p31)	1700.0000
32 - W598 (p32)	60.5000
33 - NG (p33) DISCRETE	2
34 - NHeIE (p34) DISCRETE	2
35 - WBP (p35)	370.0000
36 - D10C (p36)	1.0000
37 - FP (p37)	0.0790
38 - WOFH (p38)	379.2000
39 - CHMAT (p39) DISCRETE	1
40 - CBVC (p40) DISCRETE	1
41 - LCB (p41)	-10.0000
42 - PMF (p42)	1.1000
43 - PC (p43)	0.6700
44 - SELECTP (p44) DISCRETE	5
45 - SELECTG (p45) DISCRETE	4

Values of functional relations:	
1 - f1 = kWG - kWGREQ >= 0	63.310373
2 - f2 = D10x - D10SL >= 0	0.0516928
3 - f3 = GM > 0	4.176925
4 - f4 = PI - PIREQ >= 0	4631.7511
5 - f5 = Eact - E >= 0	577.09656
6 - f6 = Ndecks - NHPIE >= 0	1
7 - f7 = Ndecks - NHeIE >= 0	0

Values of criteria:	
1 - ERRKW (%)	2.4860957
2 - ERRPOWER (%)	10.005241
3 - ERRVOL (%)	11.771601
4 - ERRAREA (%)	14.339138
5 - ERRWEIGHT (%)	1.0124392
6 - COST	555.72545
7 - f8 = CLB <= 10	9.047619
8 - f8 = CLB >= 7.5	9.047619
9 - f9 = CBT <= 3.7	2.5519203
10 - f9 = CBT >=2.8	2.5519203
11 - f10 = CDELTAL <= 65	68.241064
12 - f10 = CDELTAL >= 45	68.241064
13 - f11 = CGMB <= 0.122	0.1060806
14 - f11 = CGMB >= 0.09	0.1060806
15 - f5 = Eact - E	577.09656

Figure 33: The prototype of surface combatant

Six optimizations were carried out for this surface combatant. The optimization characteristics are described in Fig. 34

	1st Optimization	2nd Optimization	3rd Optimization	4th Optimization	5th Optimization	6th Optimization
Tests performed	200,000	200,000	200,000	200,000	200,000	500,000
Test Table Contains	10,025	11,331	18,553	143,593	143,672	3,572
Feasible set contains	7	9	3	2,161	2,169	627
Pareto-optimal set contains	7	8	3	208	184	138
Number Generator	LP-Tau Net	LP-Tau Net	LP-Tau Net	LP-Tau Net	Windows RNG	LP-Tau Net

Figure 34: Overall characteristics of optimization procedure for surface combatant

The optimization results are illustrated by Fig.35 (with the whole set of variables for all optimizations), Fig.36 (for a selected one) and by Fig.37 (with criteria for the first optimization).

Parameters	1st Optimization	2nd Optimization	3rd Optimization	4th Optimization	5th Optimization	6th Optimization
1 - LWL (p1)	300 — 400	300 — 370	328 — 370	360 - 372	360 - 372	360 - 372
2 - B (p2)	35 — 45	35 — 45	37 — 45	39 — 42	39 — 42	39 — 42
3 - Ndecks (p3) DISCRETE	2, 3, 4	2, 3	2, 3	**2**	**2**	**2**
4 - CP (p4)	0.54 — 0.64	0.54 — 0.64	0.54 — 0.64	0.57 — 0.64	0.57 — 0.64	0.57 — 0.64
5 - CX (p5)	0.70 — 0.85	0.70 — 0.85	0.70 — 0.85	0.80 — 0.85	0.80 — 0.85	0.80 — 0.85
6 - HDKh (p6)	8.3 — 8.7	8.3 — 8.7	8.34 — 8.70	8.38 — 8.70	8.38 — 8.70	8.38 — 8.70
7 - BILGE (p7)	4.5 — 5.5	4.4 — 5.4	4.4 — 5.4	4.3 — 5.3	4.3 — 5.3	4.3 — 5.3
8 - HDKd (p8)	7.85 — 8.25	7.85 — 8.25	7.89 — 8.21	7.90 — 8.21	7.90 — 8.21	7.90 — 8.21
9 - NPENG (p9) DISCRETE	1, 2, 3, 4	1, 2, 3	1, 2	**2**	**2**	**2**
10 - eta (p10)	0.95 — 0.99	0.95 — 0.99	0.954 — 0.986	0.96 — 0.99	0.96 — 0.99	0.96 — 0.99
11 - NDIE (p11) DISCRETE	1, 2	1, 2	1, 2	**1**	**1**	**1**
12 - NHPIE (p12) DISCRETE	1, 2, 3, 4	1, 2, 3	1, 2, 3	1, 2	1, 2	1, 2
13 - WF46 (p13)	15 — 20	13 —19	13 —19	15 —19	15 —19	15 —19
14 - NP (p14) DISCRETE	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2
15 - DP (p15)	11 — 13	11 — 13	11 — 12.8	11 — 13	11 — 13	11 — 13
16 - LS (p16)	98 — 103	97 — 102	98 — 101.5	98 — 102	98 — 102	98 — 102
17 - ADB (p17)	500 — 580	493—573	493—557	510—561	510—561	510—561
18 - WIC: (p18)	43 — 44	34 — 44	34 — 43	36 — 43	36 — 43	36 — 43
19 - Nfins (p19) DISCRETE	0, 1	0, 1	0, 1	0, 1	0, 1	0, 1
20 - CSD (p20)	0.27 — 0.29	0.27 — 0.29	0.272 — 0.288	0.270 — 0.288	0.270 — 0.288	0.270 — 0.288
21 - ASD (p21) DISCRETE	27, 215	27, 215	**27**	**27**	**27**	**27**
22 - W498 (p22)	12 — 16	12 — 16	12.4 — 16	12.5 — 16.2	12.5 — 16.2	12.5 — 16.2
23 - VCG498 (p23)	-3.1 — -2.9	-3.08 — -2.96	-3.08 — -2.96	-3.07 — -2.98	-3.07 — -2.98	-3.07 — -2.98
24 - ACOXO (p24)	300 — 350	270 - 320	270 - 320	289 - 315	289 - 315	289 - 315
25 - vf (p25) DISCRETE	3.5, 5.2	3.5, 5.2	3.5, 5.2	**3.5**	**3.5**	**3.5**
26 - CDHMAT (p26) DISCRETE	1, 2	1, 2	1, 2	1, 2	1, 2	1, 2
27 - CPS (p27) DISCRETE	0, 1	0, 1	0, 1	**0**	**0**	**0**
28 - kWM (p28)	40 — 52	40 — 52	40 — 52	39 — 45	39 — 45	39 — 45
29 - W593 (p29)	12 — 17.5	12 — 17.5	12 — 17.5	14.6 — 16.5	14.6 — 16.5	14.6 — 16.5
30 - W171 (p30)	1.8 — 2.2	1.8 — 2.2	1.8 — 2.2	1.8 — 2.15	1.8 — 2.15	1.8 — 2.15
31 - VWASTE (p31)	1600 — 1800	1600 — 1800	1660 — 1780	1660 — 1780	1660 — 1780	1660 — 1780
32 - W598 (p32)	58 — 63	58 — 63	58 — 62.5	57 — 63	57 — 63	57 — 63
33 - NG (p33) DISCRETE	2, 3, 4	2, 3	2, 3	**2**	**2**	**2**
34 - NHeIE (p34) DISCRETE	1, 2, 3, 4	1, 2, 3	1, 2, 3	**2**	**2**	**2**
35 - WBP (p35)	340 — 400	340 — 390	335 — 385	332 — 365	332 — 365	332 — 365
36 - D10C (p36)	1 — 1.2	1 — 1.2	1 — 1.2	1 — 1.1	1 — 1.1	1 — 1.1
37 - FP (p37)	0.04 — 0.21	0.01 — 0.21	0.07 — 0.11	0.074 — 0.083	0.074 — 0.083	0.074 — 0.083
38 - WOFH (p38)	360 — 400	360 — 400	356 — 384	350 — 382	350 — 382	350 — 382
39 - CHMAT (p39) DISCRETE	0.93, 1	0.93, 1	0.93, 1	0.93, 1	0.93, 1	0.93, 1
40 - CBVC (p40) DISCRETE	0, 1	0, 1	0, 1	0, 1	0, 1	0, 1
41 - LCB (p41)	-11 — -9	-11 — -9	-11 — -9	-10 — -9.3	-10 — -9.3	-10 — -9.3
42 - PMF (p42)	1.05 — 1.15	1.05 — 1.15	1.05 — 1.15	1.05 — 1.15	1.05 — 1.15	1.05 — 1.15
43 - PC (p43)	0.6 — 0.74	0.6 — 0.74	0.6 — 0.74	0.59 — 0.74	0.59 — 0.74	0.59 — 0.74
44 - SELECTP (p44) DISCRETE	1, 2, 3, 4, 5, 6, 7	1, 2, 3, 4, 5, 6, 7	1, 2, 3, 4, 5, 6, 7	5, 6	5, 6	5, 6
45 - SELECTG (p45) DISCRETE	1, 2, 3, 4, 5, 6, 7	1, 2, 3, 4, 5, 6, 7	1, 2, 3, 4, 5, 6, 7	1, 5	1, 5	1, 5

Figure 35: Optimization results for the surface combatant model

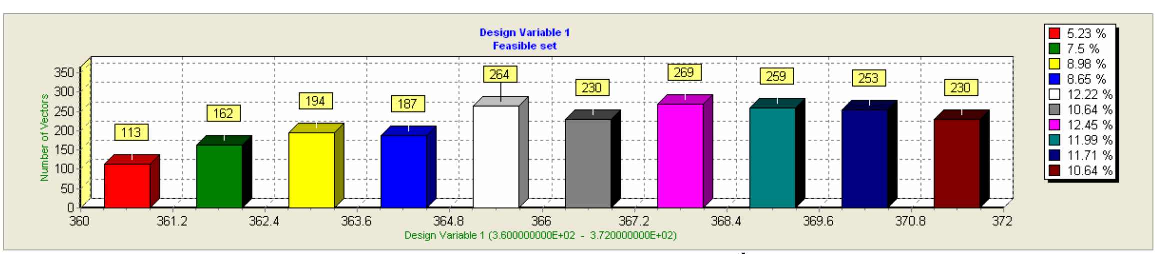


Figure 36: Feasible Set Histogram. Design Variable1 - LWL, 4th Optimization

Tests performed 200000
Feasible set contains: 7
Pareto-optimal set contains: 7
Number Generator: LP-Tau Net

Criteria		32921	42129	100762	111350	133985
Criterion #1	ERRKW (%)	67.5170	65.0741	32.4957	0.7701	31.6999
Criterion #2	ERRPOWER (%)	9.5599	31.5208	26.7154	49.7089	48.5032
Criterion #3	ERRVOL (%)	27.7329	10.2123	0.9650	16.7188	3.4904
Criterion #4	ERRAREA (%)	32.2181	12.7648	1.2090	19.5245	4.2446
Criterion #5	ERRWEIGHT (%)	-16.8812	-35.0273	-27.5743	-37.5293	-35.0323
Criterion #6	COST	593.0446	593.6998	568.6793	570.3146	548.3922
Pseudo-Criteria		**32921**	**42129**	**100762**	**111350**	**133985**
Criterion #7	f8 = CLB <= 10	8.0437	9.0826	8.8541	8.4999	8.6254
Criterion #8	f8 = CLB >= 7.5	8.0437	9.0826	8.8541	8.4999	8.6254
Criterion #9	f9 = CBT <= 3.7	2.8919	3.6964	2.8647	3.3380	3.1275
Criterion #10	f9 = CBT >=2.8	2.8919	3.6964	2.8647	3.3380	3.1275
Criterion #11	f10 = CDELTAL <= 65	65.8392	49.2311	60.5866	50.8278	47.1992
Criterion #12	f10 = CDELTAL >= 45	65.8392	49.2311	60.5866	50.8278	47.1992
Criterion #13	f11 = CGMB <= 0.122	0.1077	0.1007	0.1080	0.0890	0.0978
Criterion #14	f11 = CGMB >= 0.09	0.1077	0.1007	0.1080	0.0890	0.0978
Criterion #15	f5 = Eact - E	663.5402	1165.8918	1223.3569	1147.4750	821.7482

Criteria		143848	158349	Minimum	Maximum
Criterion #1	ERRKW (%)	40.0005	8.6022	0.7701	67.5170
Criterion #2	ERRPOWER (%)	39.1253	37.3035	9.5599	49.7089
Criterion #3	ERRVOL (%)	-6.7187	24.4463	-6.7187	27.7329
Criterion #4	ERRAREA (%)	-8.4763	29.7730	-8.4763	32.2181
Criterion #5	ERRWEIGHT (%)	-42.8251	-33.6327	-42.8251	-16.8812
Criterion #6	COST	561.3962	588.8861	548.3922	593.6998
Pseudo-Criteria		**143848**	**158349**	**Minimum**	**Maximum**
Criterion #7	f8 = CLB <= 10	7.8701	8.7423	7.8701	9.0826
Criterion #8	f8 = CLB >= 7.5	7.8701	8.7423	7.8701	9.0826
Criterion #9	f9 = CBT <= 3.7	3.6272	3.5576	2.8647	3.6964
Criterion #10	f9 = CBT >=2.8	3.6272	3.5576	2.8647	3.6964
Criterion #11	f10 = CDELTAL <= 65	59.4805	47.2711	47.1992	65.8392
Criterion #12	f10 = CDELTAL >= 45	59.4805	47.2711	47.1992	65.8392
Criterion #13	f11 = CGMB <= 0.122	0.1135	0.0895	0.0890	0.1135
Criterion #14	f11 = CGMB >= 0.09	0.1135	0.0895	0.0890	0.1135
Criterion #15	f5 = Eact - E	995.2834	732.8596	663.5402	1223.3569

Figure 37: Table of Criteria for 1st Optimization

The results of these numerical experiments show that the employed approach can be efficiently used not only for optimization search, but also for investigation of mathematical model when some constrains or criterions are not well defined and can be changed or modified in the course of optimization process

7. FORMULATION OF MULTI-DISCIPLINARY NAVAL DESIGN PROBLEM FOR A TRIMARAN

The synthesis model for trimaran ships is currently under development. The basis for the model development is R&D and design studies provided for the recent 3-5 years by NSWCCD, SAIC, KMM

and other domestic firms, as well as in Australia, Great Britain and Italy. At the synthesis level the model would include ten following variables:

Ω=ratio of center and side hull displacements
L_{ch}= length of the center hull
L_{sh}= length of the side hull
B_{ch}= beam of the center hull
B_{sh}= beam of the side hull
D= depth of the trimaran
α=ratio of the clearance between the hulls to B_{ch}
V_k= speed
β=ratio of the side hull Longitudinal position to L_{ch}
C^B_{sh} = block coefficient of the side hull

The present study has begun by developing the modules which allow calculations of various characteristics and parameters of the trimaran design. Let us define results of a one-disciplinary analysis as an objective function. For the trimaran synthesis model Criteria, Objective Functions and Restrictions would be similar to the sample model, but the modules for powering, seakeeping, structures, and payload would reflect the specifics of the trimaran ship. The powering algorithm in synthesis-level optimization task is shown in Figs. 27 and 28. Keeping in mind that the analyzed variant number in the above-demonstrated simplified models was close to 10^4, one can expect even higher variant number in trimaran design. Therefore, a direct employment of complex computer solvers (CFD, BEM, FEA) would be unrealistic for the MDO, but interpolations of the related solutions should be effected. The basic multihull resistance problems, including wave interaction between the hulls, slender hulls resistance scaling factors due to wide transom and running trim (Mizine, Amromin et al, 2004) would be used as a basis of computation of trimaran drag. Other involved disciplines are the sea keeping of the trimaran ship (for different operational requirements) and structural aspects of the design. (CFD codes and FEA would be used to build an interpolation basis). These modules would be corrected with taking into account the model test data obtained in the course of serial of model tests in NSWCCD. Weight distribution would be calculated on the basis of data for large sealift trimaran ships, Short Sea Shipping/ Theater Support Vessel and other designs. This model would be developed and further used along with a modified PSI solver.

Powering for Trimaran synthesis model

CO	Coefficient of residual resistance	WS	Wetted Surface - trimaran	Slch/sh	Slenderness - Center/Side hull
CF	Coefficient of friction resistance	WSch	Wetted Surface - center hull	Lch/sh	Length - Center/Side hull
CK	Correlation Coefficient	WSsh	Wetted Surface - side hull	Rech/sh	Reynolds number - Center/Side hull
CR	Total Resistance Coefficient	Displ	Displacement - trimaran	Re	Reynolds number - Trimaran
alfa	separation of the hulls	Displ_ch	Displacement - center hull	Sl	Slenderness - Trimaran
beta	stagger: longitudinal position of the side hulls	Displ_sh	Displacement - side hull	Res	Resistance of Trimaran
kapa	Displacement side hull/Displacement trimaran			EHP	Effective Power
Vk	Speed [Knots]			SHP	Shaft Power
				PEC	Propulsion Efficiency Coefficient

1	WS = Displ^2/3 * (-1000*kapa^2 + 450*kapa +80) [SQFT]	AA1= 9.15
2	WS = WSch + 2*WSsh	
3	Displ = Displ_ch + 2*Displ_sh	
4	Slch = Lch/Displ_ch	Variables
5	Slsh = Lsh/Displ_sh	
6	Sl = (Slch*WSch+2*Slsh*WSsh)/WS	Input data, which can be variable
7	WSch = AA1*Slch*Displ_ch^2/3 [SQFT]	
8	WSsh = (WS - WSch) / 2	Calculations
9	V = Vk*0.515/0.3048 [FT/sec]	
10	CF=f(Re)=0.075/POWER((LOG10(Re)-2),2)	
11	Rech/sh = V * Lch/sh * 100000 / 1.187	
12	Re = (REch*WSch+2*REsh*WSsh)/(WSch+2*WSsh)	
13	CK*1000 = -0.001*Lch+0.9	
14	CO*1000 =f(Sl, alfa, beta, Fn) - see Sheet "CO"	
15	CR*1000 = (CO+CF+CK)*1000	
16	Res = V^2 * WS * (CR*1000)/1000 [LB]	
17	EHP = V * Res / 550 [HP]	
18	SHP = EHP / PEC [HP]	

Figure 38: Power prediction algorithm for trimaran optimization model

Coefficient of residual resistance: CO=f(Slenderness, Separation, Stagger, Froude number)
The calculations are made by MQLT with use of trimaran model testing data
The basic calculations have to be interpolated for use in optimization procedures

			Froude numbers								
Slenderness	Separation	Stagger	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
sl=9	beta=0	alfa=1	2.00	2.50	2.80	2.50	1.80	1.20	1.00	0.90	0.85
		alfa=0.5	2.50	4.00	4.30	3.80	3.00	2.40	2.00	1.80	1.70
		alfa=1.5	1.80	2.30	2.50	2.20	1.60	1.10	0.95	0.85	0.80
	beta=1	alfa=1	2.50	3.50	3.70	3.40	2.50	1.40	0.80	0.70	0.65
		alfa=0.5	2.40	3.40	3.63	3.45	2.60	1.55	1.00	0.95	0.90
		alfa=1.5	2.40	3.35	3.53	3.40	2.40	1.30	0.75	0.60	0.55
	beta=0.5	alfa=1	1.70	2.20	2.40	2.30	1.80	1.55	1.50	1.40	1.30
		alfa=0.5	1.80	2.10	2.55	2.60	2.00	1.85	1.75	1.70	1.65
		alfa=1.5	1.70	2.40	2.60	2.20	1.70	1.35	1.25	1.15	1.10
sl=12	beta=0	alfa=1	2.00	2.60	2.80	2.40	1.60	0.90	0.70	0.60	0.50
		alfa=0.5	2.50	4.16	4.30	3.65	2.67	1.80	1.40	1.20	1.00
		alfa=1.5	1.80	2.39	2.50	2.11	1.42	0.83	0.67	0.57	0.47
	beta=1	alfa=1	2.50	3.64	3.70	3.26	2.22	1.40	1.00	0.80	0.70
		alfa=0.5	2.40	3.54	3.63	3.31	2.31	1.20	0.80	0.63	0.60
		alfa=1.5	2.40	3.48	3.53	3.26	2.13	1.10	0.70	0.60	0.55
	beta=0.5	alfa=1	1.70	2.29	2.40	2.21	1.60	1.16	1.05	0.93	0.76
		alfa=0.5	1.80	2.18	2.55	2.50	1.78	1.39	1.23	1.13	0.97
		alfa=1.5	1.70	2.50	2.60	2.11	1.51	1.01	0.88	0.77	0.65
sl=6	beta=0	alfa=1	3.50	5.00	5.60	5.00	4.00	3.00	2.30	2.00	1.70
		alfa=0.5	4.38	8.00	8.60	7.60	6.67	5.50	4.60	4.00	3.40
		alfa=1.5	3.15	4.60	5.00	4.40	3.56	2.75	2.19	1.89	1.60
	beta=1	alfa=1	4.38	7.00	7.40	6.80	5.56	3.50	1.84	1.56	1.30
		alfa=0.5	4.20	6.80	7.26	6.90	5.78	3.88	2.30	2.11	1.80
		alfa=1.5	4.20	6.70	7.06	6.80	5.33	3.25	1.73	1.33	1.10

Figure 39: Resistance coefficient as function of trimaran hulls configuration. There are dependencies on slenderness (sl), longitudinal hull position (beta), and hulls stagger – transverse position (alfa).

The user will define the set of the feasible solutions satisfying the design constrains. MDO results in finding the so-called Pareto optimal set of design solutions. Furthermore, a decision maker will be included to put the Pareto optimal solutions in a complete order, hence finding the final limited set that best satisfies the decision maker. The separate mission goals criterions at synthesis phase of the design and different disciplines like resistance, sea keeping and structural analysis at further spiral design phase are tackled separately, so that the whole problem is truly multi-disciplinary.

The project efforts include approximation of each of the objective functions with an analytical model, based on results of complex BEM, CFD and FEA models. This would produce a sensible reduction in the computational effort. It can take place also because of employment of some results of more complex theories in more simple. For example, quite smooth CFD results on monohulls trim can be employed in our quasi-linear theory (Mizine, Amromin et al, 2004) and give very good estimations for all drag components (see Fig.40) in few seconds of PC time.

It is appropriate to add that design of trimarans is a very hot topic because of their advantages in interaction with aviation and convenience with large cargo transportation.

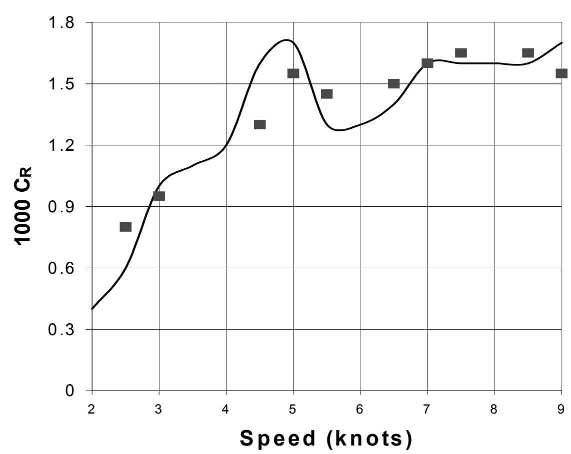


Figure 40: Comparison of computed (curve) and measured (squares) residuary drag coefficient for a fast trimaran model.

8. CONCLUSIONS

The general project objective for the present work and its eventual extension is to develop and demonstrate a multi-disciplinary computational (**MDC**) design tools that will improve the accuracy/decrease the computational cost of naval design. Combining together modern numerical techniques for solving physical problems and optimization methods, it would be possible to improve the ship design, enhancing operational performance and reducing the development costs.

The Phase I of this project is assigned to provide a feasibility of concept for design tools and algorithms. We considered the basic aspects of the suggested methodology. The entire range of mathematical issues in creating of MDC tools for Naval Design (ND) has been investigated:

- COORDINATION OF DESIGN SOLUTIONS IN MULTI-LEVEL DESIGN SYSTEMS by employment of the Lagrange multipliers was considered and illustrated by examples related to naval design.
- SELECTION OF VARIABLES AND PARAMETER SPACE INVESTIGATION with searching Pareto set of design solutions was presented. Applicability of Parameter Space Investigation method is demonstrated for series of preliminary ND tests and validated by comparing with results of publications, where multi-criteria optimization problem was solved by converting into a single-criterion optimization
- GENERATION OF COMPUTATIONAL GRIDS was considered with comparison of Pruning Algorithms (PA) and Constructive Algorithms (CA) represented by Neural Network and illustrated by optimization examples. The employment of random search training sets of points and LPτ sequence of points is described.

Comparison of PA and CA is illustrated by examples of ND which contain coupling of complex hydrodynamic problems solved with CFD and BEM codes with simple restrictions obtained from other disciplines. This comparison shown the advantages of PA combined with interpolation/approximation of preliminary obtained results in reasonably selected points.

Three practical examples of MDC in ND illustrate application of the selected approaches to MDO:

- The three-criterion Bulk Carrier Design problem with sixteen constrains related to the different disciplines.
- The six-criterion Surface Combatant Design problem with forty five variables and sixteen constrain divided into one group of rigid constrains and another group of soft (correctable) constrains. The ship model was implemented in MATLAB and several customized modules were developed and compiled into a set of dynamic link libraries to allow an interface between PSI and this ship model. The impact of optimization technique and weight selection on its result is shown. Employed computer codes are friendly interactive from designer point of view.
- Formulation of multi-disciplinary naval design problems for a trimaran finishes this Phase I project as an undertaking for the eventual Phase II project.

MDO tools development approach. This approach has the following benefits:

1. Possibility of design coordination of various subsystems' solutions in the multi-level design systems employed for ND.
2. Increase of accuracy and reduction of computational cost of MDC in ND due to rational combination of numerical solutions of complex physical problems and optimization technique.
3. Development of innovative designs for commercial and military ships as result of exploring a multi-level and multi-criteria naval design system.

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